DEPARTMENT OF COMPUTER LANGUAGES AND SYSTEMS

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FORMALIZATION OF CONCEPT-RELATEDNESS USING ONTOLOGIES: CONCEPTUAL DENSITY

applications
in the construction of lexical knowledge bases,
word sense disambiguation
and
automatic spelling correction

Eneko Agirre Bengoa

A dissertation in Computer Science

Donostia, 1998

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Dissertation written by **Eneko Agirre Bengoa,** under the supervision of **Kepa Sarasola Gabiola** and **Arantza Diaz de Ilarraza**.

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ABSTRACT

People decide in the most natural way up to which point two things are related or not. We call this ability measure of relatedness, that is, the measure of the strength for the relation between two (or more) words. In order to formalize and implement the measure of relatedness, structured lexical resources are needed. The main contributions of this dissertation are the following:

1. The formalization of knowledge-based relatedness among words and concepts.

2. A method to enrich and strengthen structured lexical resources extracted from dictionaries.

The first contribution yielded Conceptual Density, a measure of relatedness implemented on *WordNet,* a lexical knowledge-base for English. The theoretical advantages of our formalization are presented, as well as the evaluation results on two practical tasks. On the one hand, we have performed free-text Word Sense Disambiguation, applying Conceptual Density on all nouns appearing in a public-domain English corpus. Our results compare favorably with two other state-of-the-art techniques applied to the same corpus. On the other hand, we also tackled the automatic correction of spelling errors for English, but in this case, using Conceptual Density alongside other complementary knowledge sources and techniques, i.e. Constraint Grammar and word and co-occurrence statistics. The implemented system demonstrates that the intended correction proposal can be automatically selected with high precision.

As regards the second main contribution, it is well known that the information extracted form dictionaries has its shortcomings. The hierarchies obtained are usually hierarchies of words, not of word-senses. Moreover, the hierarchies tend to be shallow and small, with unsatisfactory structure in the higher part. The method presented in this dissertation shows that this shortcomings can be overcome on a French monolingual dictionary, *Le plus Petit Larousse*. The method comprises techniques to sense-disambiguate the genus terms in the definitions, thus producing hierarchies of word-senses, and techniques to link the senses of the entries in the target dictionary to the senses in a lexical knowledge-base in a different language, via a bilingual dictionary. Conceptual Density is the key component in both tasks. The proposed method is also used to solve the difficulties posed by the cycles in the hierarchies and the isolated entries which are unconnected. The method enables the production of high quality structured lexical resources for non-English languages, in addition to multilingual links among resources in different languages.

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To collaborate with German in the hot desert has also been decisive
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If some helped researching, others managed to keep me away, for my own benefit.

parents and sister; the *koadrila* in eibar; those in my flat who promote laziness;
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military service group (drawing posters is fun!).

after all, ana, not everything is work, is it?

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LIST OF COMMON ABBREVIATIONS

AR. Association Ratio

CD. Conceptual Density

CG. Constraint Grammar

DKB. Dictionary Knowledge-Base

LKB. Lexical Knowledge-Base

LPPL. *Le Plus Petit Larousse*

MI. Mutual Information

NLP. Natural Language Processing

OFED. Oxford French/English Dictionary

WN. WordNet

WSD. Word sense Disambiguation

I.Chapter

INTRODUCTION

II.Motivation

People decide in the most natural way up to which point two things are related or not. What is more related to sheep: cow, codfish or radio? We have no problems to recognize the relations existing among the objects involved, and we are readily prepared to answer such questions. However, as it happens with most abilities connected to common sense, it is very difficult to make computers show this ability. They lack the clues to answer this kind of questions. They do not know what sheep, cow or radio are, nor do they know which are the relations among them. Were they able to answer such questions, computers could get a grasp of this area of common sense, and this could be applied to several interesting applications. We will focus on Natural Language Processing (NLP). As many people think, the key of semantic processing lies in the ability to answer such questions regarding the relatedness degree. We will call this ability <u>relatedness</u>, that is, the measure of the strength for the relation between two (or more) words. This measure is usually defined just for nouns.

In literature, different ways to formalize relatedness have been studied. In some works, only relatedness between words has been developed, but many others work with word senses or concepts[1]. The first ones do not distinguish between the different senses of the word *bank*, for instance. The latter, on the contrary, asked whether the words *bank* and *river* are closely related or not, would answer that "it depends": if this *bank* is riverside, then yes, but if it is a building having to do with money, then no, these are not so closely related. From our point of view, the formalization for word senses is more interesting than just the relatedness between words.

[1] Word sense and concept will be used as equivalent terms in this dissertation.

Formalizations can be also classified according to the lexical resource they use:

- Those using collections of written texts, corpora
- Those using dictionaries, specially the definition texts
- Those using structured knowledge, such as Dictionary Knowledge Bases (DKB), Lexical Knowledge Bases (LKB) and ontologies

After studying the three resource types, we deemed most reasonable to base our formalization on structured knowledge. All lexical resources keep interesting information, which is highly complementary. However, relatedness measures based on ontologies have the strongest tradition, rooted in research on psychology and artificial intelligence. The fact of having a wide coverage LKB like WordNet (Miller et al. 1993b) accessible has allowed us to apply our theoretical ideas on practice, as we implemented our measure of relatedness on this knowledge base. We will study several measures based on all different kinds of lexical resources in section III.A, and the reasons to prefer those based on ontologies will be exposed in section III.D. The measure of relatedness introduced in this dissertation is called Conceptual Density (CD), and it is based on the hierarchy of ontology concepts[2]. Even if it has been implemented on the hierarchy of WordNet, it can be applied on any lexical resource as long as it supplies concepts structured on a hierarchy.

The measure of relatedness among word senses is crucial or at least helpful for many applications, such as disambiguation of syntactic structures, word sense disambiguation, ontology building, learning of selectional restrictions, merging of ontologies, evaluation of ontologies, information retrieval, document retrieval and classification, concept clustering, automatic text correction, as well as general semantic interpretation.

Relatedness often appears closely linked to Word sense Disambiguation (WSD), and we have actually used this application to evaluate our formalization. We have used Conceptual Density to disambiguate among the senses of nouns appearing in free-running texts. This field is currently one of the most active areas in NLP, and continues to pose an open problem. The machine-translation systems built in the sixties, for instance, could not cope with word sense ambiguity, and that was one of the main reasons for their failure. As the implementations of relatedness started to use broader information sources, better results have been achieved in word sense disambiguation. Even

[2] Concepts that will be linked to the word senses in the lexicon.

if the current technology is not ready-usable in real applications, word sense disambiguation with a manageable error-rate for free-running text might be at hand in the near future.

The most extended approaches to WSD represent polisemy and homonymy using a closed list of word senses, and usually claim that knowledge-poor[3] techniques would suffice for the task. Of course, these mainstream approaches have been heavily disputed. On the one hand, there are those that do not conceive WSD separated from general NLP, as it would first require that all difficult problems in NLP were solved. They think that the (knowledge-based) advances on NLP will dilute the word sense ambiguity problem naturally. On the other hand, there are those who dispute the closed-list model, and advocate the dynamic nature of the lexicon. According to them, there is no way to state differences between word senses without first understanding processes such as metonymy and metaphor. Some skeptics go further, and claim that it is impossible to draw lines between word senses, and question the existence of word senses as discrete entities. In our opinion, these are all valuable criticisms that have to be taken into account. Ideally all these ideas should be integrated into the WSD system (and, at the same time, WSD should be tightly integrated with general LNP), but it can not be denied that, meanwhile, interesting results are being obtained using just the most simplistic approaches. More recently, it seems that the discussion has been taken to the practical side. For instance, Kilgarriff, who doubts about the existence of word senses (Kilgarriff, 1997a), has organized the Senseval[4] competition on WSD in 1998.

One of the most important goals of our research group is the development of help-systems for text comprehension and production. In this sense, we developed the commercial spelling checker/corrector for Basque "Xuxen". When finding a misspelling, spelling correction programs try to figure out the correct word, producing a list of correction proposals. It is up to the human user to choose the correct proposal. Even if this might suffice for text-processors, for other applications the program itself has to choose the correct proposal. One example of such an application is optical character recognition. It is known that when a text is scanned, optical character recognition introduces some errors (for example, the 'I' at the beginning of a word is often recognized as an 'l') and, in consequence, a post-process has to be performed in order to correct the recognition mistakes, usually involving a person that uses a spelling-corrector. In order to check whether such human post-processing can be eliminated or not, we have developed a system for <u>automatic text-correction</u>, which uses syntactic tools developed in our group and

[3] We use knowledge-poor as opposed to knowledge-based approaches. In other words, we can say that, currently, techniques using extensive knowledge are more popular and successful than knowledge-intensive methods.

[4] http://www.itri.bton.uk/events/senseval/

Conceptual Density. Incidentally, we have been able to test our relatedness measure in a different task.

Another important motivation of this thesis is the production of structured lexical resources. During the eighties, the NLP community, which was focusing mainly on syntactic issues, noticed the need of wide and rich lexical resources. If NLP-based applications were to deal with real texts, wide coverage lexicons were in hard need. Besides, it was found that many linguistic phenomena that had been described using complicated syntactic rules, had a lexical origin. Accordingly, the lexicon evolved from being a plain list of words to a rich structured system of words and word senses. Seeing things as they were, the research groups began to build these both rich and wide-coverage lexicons manually. The amount of information to be coded is really huge, and it requires quite a few person-years, which were available just to a handful of wide-scale projects, like for example, CYC (Lenat, 1995), EDR (Yokoi, 1995; EDR, 1993) or WordNet. As an alternative to fully-manual encoding, automatic or semi-automatic means to produce lexicons have also been considered, focusing on the information extraction from other lexical resources, namely, corpora and dictionaries.

Dictionaries have often been the starting point to extract Lexical Knowledge-Bases (LKB). From all the kinds of information extracted, from a lexical-semantic point of view, the most outstanding ones have been the hierarchies. Unfortunately, most research groups were only able to get hierarchies of words, as they were not capable of discriminating automatically the appropriate word sense involved in a certain node of the hierarchy. One important exception is the work (Bruce et al., 1992) done on the LDOCE dictionary (Procter, 1978). In this case word sense hierarchies were automatically built using the information that was coded in this specific dictionary to perform the disambiguation. Most of the extracted LKBs have been for English, as well as the ontologies and the LKBs that were built by hand. This leaves all other languages in a weak position when facing real-text NLP. There are two complementary solutions to this unwanted situation:

- To use the corpora and dictionaries that are available for each language in order to extract LKBs for that language.
- To use the knowledge already coded in English LKBs in order to create LKBs in a different language.

In other words, available lexical resources for the given language have to be used, of course, but whenever is possible and appropriate the knowledge coded in English LKBs should be translated and reused. In our opinion, our formalization of relatedness can help in both complementary approaches, as we will show in chapter VI.

The two main motivations for this dissertation, that of formalizing a measure for relatedness and that of building structured lexical resources, are interrelated. Relatedness for a given language can not be implemented if there are no structured lexical resources for that language, especially LKB and ontologies. Besides, it is difficult to devise means to automatically create structured lexical resources without the help of relatedness measures. Using the existing LKBs and ontologies for English it is possible to define the relatedness for English words and word senses. If this relatedness could be used to speed up the construction of structured resources for other languages and to link them to English resources, it would be possible then to absorb all the richness in English resources, and all these rich resources would be available for other languages. Following this direction of research, we performed two main tasks. On the one hand, we linked the entries of the French dictionary *Le Plus Petit Larousse* (LPPL, Larousse, 1980) to the entries in the English LKB WordNet, at the sense level, that is, French word sense linked to English word sense. On the other hand, both the information in the dictionary and the links built to WordNet were used to sense-disambiguate the hierarchies extracted from LPPL.

During the work that produced this dissertation, there were no wide and structured lexical resources for any languages other than English. We therefore defined relatedness for English senses, which we applied to word sense disambiguation and text-correction on English texts. Regarding the construction and enrichment of LKBs, our group had already extracted much lexical information from a French dictionary, producing a first version of a LKB. This dissertation describes the work performed on this LKB in order to enrich and reorganize its hierarchies. Nevertheless, Basque is the target of most research in our group. All methods and techniques developed in this dissertation were designed general enough to be used in the construction of structured lexical resources and in the implementation of a relatedness measure for Basque or any other language.

III.Goals

Answering the main motivations, the formalization of relatedness and the building of structured lexical resources, we set two main objectives to this thesis:

1. Theoretical: to define a measure of the relatedness among concepts and words based on knowledge.

2. Practical: to develop techniques to enrich and strengthen non-English structured lexical resources.

Both goals involve lexical resources. Regarding the theoretical goal, we will try to take advantage of existing structured lexical resources so as to model a specific inference type: the relatedness measure. The practical goal is concerned with the building of richer lexical resources, from dictionaries to LKBs.

In order to achieve these goals, we set three main tasks:

1. Design and implement Conceptual Density based on WordNet.
2. Link, at word sense level, the entries in the French dictionary *Le Plus Petit Larousse* to WordNet.
3. Disambiguate and strengthen the word sense hierarchies in the Dictionary Knowledge-Base already extracted from *Le Plus Petit Larousse*.

In order to accomplish tasks 2 and 3 it has been necessary to use Conceptual Density. We have to point out that once a strong sense-disambiguated hierarchy for French is constructed, it will be possible to apply Conceptual Density directly on this hierarchy, obtaining a relatedness measure for French. The following <u>hypotheses</u> is behind our approach:

> In order to disambiguate and enrich non-English LKBs, language-external knowledge is needed, which can be readily acquired via multilingual links (usually to English).

Besides tasks 2 and 3, we have applied and evaluated Conceptual Density on two other practical applications. We therefore performed two more tasks:

4. Application, tuning and evaluation of Conceptual Density: word sense disambiguation of nouns in running text.
5. Application and evaluation of Conceptual Density: automatic spelling correction.

In order to accomplish English WSD, we just used the implementation of Conceptual Density on WordNet. Besides the evident interest of WSD, we used it to evaluate our relatedness formalization. In fact, there is no agreed procedure to directly evaluate relatedness, and we deemed better to evaluate it on a practical and comparable application.

In order to be able to perform automatic text-correction, we have used different knowledge resources, apart from Conceptual Density, including, syntactical knowledge and statistical models of word and co-occurrence frequencies.

IV.Structure of the dissertation and English version availability

Main goals of dissertation	Tasks		Original Chapters	Whole chapter in English	Appen dix	Paper code
		I	Introduction	YES		
		II	Lexical resources	YES		
To define a measure of the relatedness among concepts and words based on knowledge.	Design and implementation of Conceptual Density based on WordNet.	III	Relatedness and Conceptual Density	YES		B.1 A.1 A.2 A.3
	Application, tuning and evaluation of Conceptual Density: word sense disambiguation of running text.	IV	Word Sense Disambiguation	NO	A	A.1 A.2 A.3
	Application and evaluation of Conceptual Density: automatic text-correction.	V	Automatic Spelling Correction	NO	B	B.1 B.2 B.3 B.4
To develop techniques to enrich and strengthen non-English structured lexical resources.	Linking, at word sense level, of the entries in the French dictionary *Le Plus Petit Larousse* to WordNet. Disambiguation and strengthening of the word sense hierarchies in the Dictionary Knowledge-Base already extracted from *Le Plus Petit Larousse.*	VI	Enriching the Dictionary Knowledge Base	NO	C	C.1 C.2
		VII	Conclusions	YES		

1st table: Structure and goals of the dissertation, including availability of the English version as a chapter or collection of papers.

Code	Erref	Title	Chapters
A.1	Agirre & Rigau, 1995	A proposal for Word Sense Disambiguation using Conceptual Distance	III and IV
A.2	Agirre & Rigau, 1996a	Word Sense Disambiguation using Conceptual Density	III and IV
A.3	Agirre & Rigau, 1996b	An Experiment on Word Sense Disambiguation of the Brown corpus using WordNet	III and IV
B.1	Agirre et al., 1994b	Conceptual Distance and Automatic Spelling Correction	III and V
B.2	Agirre et al., 1995	Lexical-Semantic Information and Automatic Correction of Spelling Errors	V
B.3	Agirre et al., 1998b	Towards a Single Proposal in Spelling Correction	V
B.4	Agirre et al., 1998c	Towards a Single Proposal in Spelling Correction	V
C.1	Rigau & Agirre, 1995	Disambiguating bilingual nominal entries against WordNet	VI
C.2	Rigau et al., 1997	Combining Unsupervised Lexical Knowledge Methods for Word Sense Disambiguation	VI

2nd table: Papers related to the dissertation.

The goals and tasks of this thesis, including their relation with the contents of each chapter, the availability of the English version of the chapters and the related papers (organized in appendices) are summarized in table 1.

The chapters without English translation are covered in the published papers which are included in the appendices[5]. There is one appendix for each chapter without English translation available. The papers have been coded using the appendix where they belong. The full list of papers related to this dissertation is shown in table 2, ordered according to the appendix.

Following this introductory chapter, **chapter II** deals with lexical resources. After noting the current importance of lexical resources in Natural Language Processing, the most influential and widely known resources are introduced. In the English version, only the corpora, dictionaries and structured resources that were actually used in this dissertation are mentioned.

In **Chapter III** (Relatedness and Conceptual Density) we study different ways of measuring the degree to which words and word senses are closely related and we introduce the most important contribution of this dissertation, Conceptual Density. Before presenting Conceptual Density, we study other formalizations of relatedness. When presenting the implementation of Conceptual Density, we introduce some parameter and variants that have to be evaluated empirically. Finally, we defend the superiority of ontology-based relatedness, and among ontology-based formalizations, the advantages of Conceptual Density. A full English version of this chapter is available.

In **chapter IV** (Word Sense Disambiguation) we evaluate Conceptual Density in a practical application, and, along the way, we adjust the parameters of Conceptual Density mentioned in the previous chapter, considering the results of this application. Even if the previous chapter defends the theoretical and practical advantages of Conceptual Density, we wanted to show that it also attains good results in practice. In Word sense Disambiguation we have to decide which of the senses for a word was intended for a given test occurrence. Almost all measures of relatedness have been applied to Word sense Disambiguation (mostly in noun disambiguation), and, furthermore, they have been sometimes designed specifically for this purpose. This chapter will start with a study of antecedents, underlining the need of different knowledge sources. Afterwards, we will explain the design of the experiments and the algorithm used to disambiguate with Conceptual Density. The experiment was set on an already disambiguated corpus, so as to automatically measure the precision of the system. From this corpus, we chose four text-sets, and we disambiguated all nouns

[5] The papers can also be accessed in http://ixa.si.ehu.es/.

in the sample (around 2.000 nouns), choosing the word senses from WordNet. A specific section is devoted to study the effects of the parameters and variants of Conceptual Density, and to choose the best values for the parameters. After evaluating the results, we will compare them to those of other methods. We have implemented two other ontology-based methods, obtaining worse results. Finally, the contributions of this chapter are outlined.

This chapter is not available in the English version, but it is fully covered in the papers (Agirre & Rigau, 1995; 1996a; 1996b). The first paper (Agirre & Rigau, 1995) presents some preliminary experiments, which were completed afterwards with the experiments presented in the second paper (Agirre & Rigau, 1996a). Finally, a slightly more extended version was published as an internal report (Agirre & Rigau, 1996b).

In **chapter V** (Automatic Spelling Correction) we have developed another practical application, that of automatically correcting spelling errors. In this chapter we introduce the implementation and the design of the system that tries to choose the correct proposal among a set of correction proposals. Firstly we present the literature on this subject. Afterwards, we introduce the results of the feasibility study on semantic and syntax-based correction. We concluded that it was absolutely necessary to include semantic knowledge, and put forward a proposal for the use of relatedness measures on the LKB built from *Le Plus Petit Larousse*. In the following section, the method for automatic correction is proposed, which is based on syntactic knowledge, semantic knowledge (provided by Conceptual Density for nouns) and corpus-based statistical techniques. Next, the design of the experiments is presented alongside the evaluation and comparison with others. Two kinds of corpora were used: one in which we introduced spelling errors artificially, and another with real spelling errors. Finally, the contributions of this chapter are summarized.

Regarding the English version, this chapter is fully available in the papers (Agirre, 93; Agirre et al., 1994b; Agirre et al., 1995; Agirre et al., 1998b; Agirre et al., 1998c). The preliminary ideas were presented in Spanish in (Agirre, 1993), specifically the feasibility-study and the preliminary proposal for using the knowledge in the French LKB. A reduced version was published in (Agirre et al., 1995). The proposal for using the relations in the LKB was further elaborated in (Agirre et al., 1994b). The design of the correction system and the actual experiments are described in (Agirre et al., 1998b; 1998c), being the latter the final version.

Chapter VI (Enriching the Dictionary Knowledge Base) tackles the other main objective of this dissertation, namely, that of building LKBs for non-English languages. First of all, lexical knowledge acquisition literature is reviewed, including multilingual resource linking, and the extraction of hierarchies from dictionaries. Hierarchies are usually extracted from dictionaries by analyzing the definitions of the word senses and detecting the hypernymy relation between the entry being defined and a distinguished term in the definition called *genus*. Special attention is paid to the problems presented by the hierarchies extracted from dictionaries. On the one hand, hierarchies are not usually sense-disambiguated. On the other hand, hierarchies tend to be shallow and isolated from each other, and to exhibit coherency problems in the top layer. Part of the problems of shallowness and isolation is caused by the cycles in the extracted hierarchies and the fact that some word senses are left out of the hierarchies (generally those defined using special relators, which do not contain a genus). Our position and proposal to overcome these problems is presented next.

In order to check whether it is possible to strengthen the construction of LKBs or not, we have studied the DKB extracted form *Le Plus Petit Larousse*. So as to make this DKB a LKB usable in NLP, we have to solve the shortcomings explained above. We propose an integrated solution method. Firstly, we studied the definitions producing cycles in the hierarchy and the definitions with specific relators, and we linked all these entries to an external LKB, WordNet (in fact, we linked all entries in LPPL). These links will enable us to integrate the mentioned problematic definitions in the overall hierarchies. Secondly, we automatically disambiguated the hierarchies, producing a word sense hierarchy. Finally, we used the LPPL-WordNet links to connect all the isolated hierarchies (including those produced by breaking the cycles and by specific relator definitions) taking WordNet as a reference. In other words, we connected the isolated hierarchies using the WordNet hierarchy. By the way, the top layer of WordNet is incorporated in the extracted hierarchy, solving the lack of coherence in hierarchies extracted from dictionaries.

In order to link the word senses of the DKB extracted from LPPL to WordNet, we used a bilingual dictionary and Conceptual Density, so that we can assign one WordNet concept (or more) to each word sense in LPPL. So as to disambiguate the hierarchy, we will use both the knowledge in the dictionary itself and the link to WordNet. We have implemented several independent techniques for disambiguation, including Conceptual Density, which were combined using a voting strategy.

This chapter is not fully covered in English. The work on cycles and the treatment of specific relators is not published yet in English. The two papers related to this chapter cover the method to link LPPL to WordNet (Rigau & Agirre, 1995) and the method to disambiguate the hierarchies extracted from LPPL (Rigau et al., 1997). The latter has been further improved as explained in

(Rigau et al., 1998) but these improvements have not been covered in the present dissertation. The results for the connection of the isolated hierarchies are unavailable in English.

In the **last chapter** we summarize the contributions made, organized by chapters, and propose further work.

V. Chapter

LEXICAL RESOURCES USED

V.A. Introduction

Lexical resources have been classified according to the following criteria:

1. Corpora
2. Dictionaries
3. Structured resources: Dictionary Knowledge Bases and Lexical Knowledge Bases
4. Structured resources: Ontologies

The order is given by the degree of elaboration. In corpora, there is only raw information about words. In dictionaries, the lexicographers include part of speech, usage codes, subject codes, definitions, examples, etc. Apart from words, we can also find word senses. Dictionary Knowledge Bases (DKB) try to make explicit the information implicit in dictionaries, especially in the definition text, and gather lexical information about words. Lexical Knowledge Bases (LKB) aim at providing all information that a system performing NLP needs about words in order to understand and produce texts. Ontologies, are conceptualizations about the world or a specific field, and try to represent all that needs to be known (entities, events, reasoning, … common sense) for a given or general application.

For the sake of this dissertation, and specially in chapter III, we will refer to ontologies on a more general sense, which includes all structured lexical resources, that is, DKBs and LKBs. The main reason is that we will be focusing on a relation (*is-a*, hypernym, superclass) that is common to all structured lexical resources. In ontologies, we find hierarchies of concepts, and in DKB and LKBs hierarchies of word senses. The relatedness measure that we will define can be equally applied to any of them. For the same reason, we will use word sense and concept in an interchangeable way.

Regarding the lexical resources that were used in this dissertation, WordNet is, without any doubt, the most important resource, as we will implement relatedness over the relations in WordNet. As for corpora, we have used SemCor to evaluate the results in the disambiguation of words (cf. chapter IV), and the Brown and Bank of English corpora for the evaluation of automatic correction (cf. chapter V). In chapter VI we will enrich the DKB which has been extracted from the *Le Plus Petit Larousse* dictionary, using also the *Oxford French/English Dictionary*. We will look at each resource closer in the next sections.

V.B. Brown and Semcor

The Brown corpora (Francis & Kucera, 1967) comprises around 1.000.000 words from the English of the United States. It has been taken from several samples of different written genres. Some of the examples of the genres are the following: *press-reportage, press-editorial, learned-scienc* and *humour* .

Semcor is a subset of the Brown corpus, which has been tagged with semantic information by the same team that designed WordNet (Miller et al. 1993). It includes 186 texts from the Brown corpora, and all adjectives, nouns, verbs and adverbs are tagged with the corresponding word sense from WordNet. We can see some data about this corpus in table 1. Except for a few words, all are tagged with an single sense. Both Brown and Semcor are freely available.

Quantity of words	359.732
Tagged with word sense	192.639
Tagged with multiple word senses	666

3rd table: Data on Semcor

In this corpus, the sentence "*The conductor said to Ritchie:*" is represented as follows (tagged according to WordNet version 1.4):

```
<s>
<stn>50</stn>
<wd>The</wd><tag>DT</tag>
<wd>conductor</wd><sn>[noun.person.1]</sn><tag>NN</tag>
<wd>said</wd><mwd>say</mwd><msn>[verb.communication.0]</msn><tag>VBD</tag>
<wd>to</wd><tag>TO</tag>
<wd>Ritchie</wd><df>person</df><sn>[noun.Tops.0]</sn><pn>person</pn><tag>NP</tag>
<wd>:</wd><tag>:</tag>
</s>
```

The tags are given using SGML. Word-forms are between <wd> </wd>, syntactic category is given between <tag> </tag>, and the semantic tag between <sn> and </sn> . For example, the word *conductor* is a noun (NN) and in this sentence, the sense it corresponds to is 1.noun.person, that is, the first sense of *conductor* with person as semantic code (we will refer to semantic codes from

WordNet in V.D). In the case of names, the semantic tag depends on the entity to which the proper noun refers to. For example, *Ritchie* is assigned person.

V.C. Bank of English

The COBUILD project led by the dictionary publishing company Collins[6], includes a corpus to monitor the development of English, which was built with the help of the University of Birmingham[7]. In 1996, the corpus had 320 million words and is currently under development. This corpus is not freely available, and permission has to be asked in order to see parts of the corpus.

V.D. WordNet

So as to implement the relatedness measure defined in chapter III, we had to choose a convenient structured lexical resource. WordNet (Miller et al. 1993b) has a very wide lexical coverage (126.520 words), best from freely available ontologies[8]. That was the main reason to choose WordNet. The other candidates were Mikrokosmos and Sensus. The first one has rich relations between concepts, but the lexicon is quite limited (they do not specify the amount of words, but it contains 4.500 concepts). The latter, was created joining semi-automatically Mikrokosmos and WordNet. It includes an interesting amount of words (90.000), but some errors were introduced in the hierarchy by the automatic joining algorithm. Unfortunately, no error-rate is given (Knight & Luk, 94). Finally, we have to point out that WordNet is very popular in NLP research (a full list of papers can be found in the WordNet web page) and that anyone can retrieve it via Internet[9].

WordNet is a LKB for English from the United States. It was designed following psycholinguistic principles. Each part of speech (nouns, verbs, adjectives and adverbs) is organized as an isolated relational system. These relational systems have synonym sets (*synset*) as conceptual units. If a word has multiple senses it will appear in several synsets, and if it has a single sense, in a single synset. For instance, *woman* has four senses, with different synonyms in each one:

```
1. woman, adult female
2. womanhood, woman
3. charwoman, char, cleaning woman, cleaning lady, woman
4. woman ((informal) a female person who plays a significant role)
```

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6 http://titania.cobuild.collins.co.uk/

7 http://titania.cobuild.collins.co.uk/boe_info.html

8 Most of wide coverage ontologies are not freely available. CYC and EDR are available, though considerably expensive. MindeNet is not available at all. Other ontologies are for internal use, and they are not prepared to be released (for example, NounSense).

9 http://www.cogsci.princeton.edu/~wn

The 4th sense has no synonyms, and therefore, a gloss is included (these glosses can also be found for the rest of senses).

There are other lexical-conceptual relations between nominal synsets (see table 2). In the case of nouns, hipernymy is the most important, as it organizes the noun hierarchy. For instance, the word senses of *woman* have the following hypernyms:

```
woman, adult female                            => female, female person
womanhood, woman       => class, social class, socio-economic class
charwoman, char, cleaning woman, cleaning lady, woman     => cleaner
woman                                          => female, female person
```

The rest of the relations include meronymy and antonymy, but they are not so systematically developed. The only relation which is not between nouns is attribute, as it relates nouns and adjectives. For example, an attribute of *canary* is to be *small*. Each relation has also its inverse relation.

We can see the data regarding nouns for WordNet version 1.5 in table 4. Nouns have an average of 1,22 senses. Each synset has an average of 2,63 relations, which are basically hipernymy and hiponymy. Half the synsets have a relation of meronymy or holonymy, and the rest of relations appear scarcely.

		Amount	Per word	Per Synset
Nouns		87.671		
Synsets		60.631	1,22	
Relations	Hypernymy/hyponymy	122.246		2,01
	Meronymy/holonymy	35.067		0,58
	Antonimy	1.713		0,03
	Attribute	645		0,01
	Total	159.670		2,63

4th table: Some data of WordNet 1.5 for nouns

Nominal synsets in WordNet are structured in 26 semantic fields. These fields are listed in table 5. The sense of a noun in WordNet can be indicated directly, e.g. the third sense of *conductor*, or indirectly as referred to a certain semantic field, e.g. the first sense for *conductor* from the *noun.person* semantic field. Among semantic fields, *noun.Tops* is special, as it gathers the synsets in the upper layer of the hierarchy.

noun.Tops	noun.feeling	noun.possession
noun.act	noun.food	noun.process
noun.animal	noun.group	noun.quantity
noun.artifact	noun.location	noun.relation

noun.attribute	noun.motive	noun.shape
noun.body	noun.object	noun.state
noun.cognition	noun.person	noun.substance
noun.communication	noun.phenomenon	noun.time
noun.event	noun.plant	

5th table: Semantic codes for nouns in WordNet

V.E. LPPL

The French dictionary *Le Plus Petit Larousse* (Larousse, 1980) is a monolingual dictionary. The data for this dictionary is shown in table 6. Our research team has carried out cosiderable research on this dictionary. First of all, we developed a Lexical Data-Base with all the information in the dictionary: entry, word sense number, part of speech, usage field, definition text and examples. The definitions were syntactically analyzed, and lexical-semantic relations were extracted. In the case of nouns, the extracted relations are the following: synonymy and antonymy, hipernymy, meronimy, lack-of, refer-to, derivation and several case relations. The extracted relations were used to build a DKB, structured as a semantic network.

	Total	Nouns
Entries	15.953	10.506
Defined word senses	22.899	13.740
Words in dictionary definitions (total)	97.778	66.323
Length of definitions (average)	3.27	3.82

6th table: Data for LPPL.

V.F. OFED

Oxford French-English Dictionary (OUP, 1989) is a bilingual dictionary of medium size. We only have the French-English part available in the machine-readable format. Table 7 shows the data for this dictionary. The dictionary has 13.030 entries. Each entry can have a single sense for the source word, or it can list more than one sense. We will call each of this bilingual senses subentry. For instance, the entry for the word *maintien* contains two subentries:

maintien n.m. (attitude) bearing; (conservation) maintenance

maintien 1: n.m. (attitude) bearing
maintien 2: n.m. (conservation) maintenance

The bilingual dictionary has 16.917 of such subentries for nouns. From another point of view, the dictionary contains 13.030 French words and 11.969 English words in the dictionary (see table 7).

	Amount of entries	Amount of subentries.
Total	21.322	31.502
Nouns	13.030	16.917
English nouns	11.969	–

7th table: Data for the bilingual dictionary OFED

The subentries include several fields: part of speech (mandatory, for instance, masculine noun, *n.m.*), semantic field (optional, it can be only one of 20 fields, for example, *comm.* in the example below, meaning commercial), a French clue (optional, for example, *attitude* and *conservtion* in the above examples, or *ressources* below), and last, but not least, the mandatory English translation or translations. The semantic field and the French clue help the user to choose the appropriate bilingual sense (subentry) for the French entry, in order to select the translation for the intended sense.

folie 1: n.f. madness
provision 1: n.f. supply, store
trésor 2: n.m (ressources) (comm.) finances

VI. Chapter
RELATEDNESS AND CONCEPTUAL DENSITY

Similarity plays a fundamental role in theories of knowledge and behavior. It serves as an organizing principle by which individuals classify objects, form concepts, and make generalizations.

(Tversky, 1977)

The main object of this chapter is to define knowledge-based concept relatedness, by designing and implementing Conceptual Density, based on WordNet. First of all, we will present relatedness and review the most important literature on this subject, classified according to the used lexical resource. In the following section, we will present Conceptual Density and its predecessor, Conceptual Distance, both based on ontologies. On section C the implementation using WordNet will be put forward. Next, section D will show the more relevant features of Conceptual Density, comparing it with the other approaches to relatedness.

VI.A. Introduction and antecedents

Before going further in the object of this chapter, we want to define the terminology used in this work, so as to clarify the misunderstanding about similarity in the literature. The bases of this work are two main ideas, which are often confused: **similarity** and **relatedness**. The first one applies to two things that are similar one to the other, for example, a fork and a spoon. The second one is used to state that both things are related, for instance, a fork and a steak. Two similar things are related, indeed, but on the contrary, two related things do not have to be similar. In the literature, similarity is widely spread, but it is often used where relatedness should appear. We believe that in general we can talk about relatedness, being similarity a certain kind of relatedness. In some works about ontology **semantic distance** has been opposed to similarity and relatedness: two concepts with high similarity have a short semantic distance between them. Similarity and semantic distance are inversely related, and therefore, it is not necessary to define semantic distance. In the present dissertation, semantic distance will not be described, but **conceptual distance** will, as an specific implementation and measure of relatedness.

Many people think that relatedness is one of the keys to understand natural language. Key to the understanding or not, many applications of Natural Language Processing use implementations of relatedness: automatic correction (see chapter VIII), information retrieval, document indexing and retrieval (Sussna, 1993), clustering (Schütze 1992a; 1992b), disambiguation (e.g. of syntactic ambiguity –see for example prepositional phrase attachment ambiguity (Resnik, 1993)– or word sense disambiguation, cf. chapter VII), in the construction of ontologies (when constructing taxonomies –cf. chapter IX– , when learning selectional restrictions (Grishman & Sterling, 1994), when merging ontologies (Knight & Luck, 1994; Utiyama & Hasida, 1997), in ontology evaluation (Rada et al., 1989)), and also in semantic understanding (EDR, 1993).

That is why literature regarding relatedness is so wide; seldom it is the main subject of papers, and only from time to time is referred to. Most of the time the paper deals with an application which implicitly uses a measure of relatedness, without defining it as such.

It is not an easy task to classify the research on relatedness, not only because of the sheer quantity of it, but also because of the very different approaches used. In other words, it seems that each research group has found its own formalization of relatedness. All formulation have weak and strong features, which could mean that this field has not reached its maturity, but it is, nevertheless, understandable, if we bear in mind that each research group has studied relatedness from a different angle, depending on the target application. Although it is not the goal of this dissertation to examine all of them in depth, we will try to classify and study the best known and those which are more related to our work. We have used a general criterion to arrange them, depending on the resource used: ontology, electronic dictionary, corpus or a combination of them.

Other concepts have also been used for the classification of the works. To begin with, we will set the following difference regarding the relatedness between two words or two concepts:

1. **Paradigmatic relation**: As regards linguistics, it holds when a word can be substituted for another one in a sentence. Conceptually, given a specific ontological world, it happens when both concepts are of the same type or class. This is understood as similarity, since similar concepts tend to be classified under the same class.

2. **Syntagmatic relation:** As far as language is concerned, it holds when two words appear in the same textual context. In a pair of coordinates, we can say that if the paradigmatic relation is vertical, the syntagmatic one is horizontal (UZEI, 1982). Conceptually, even if they are concepts of different kinds, a relation exists between them. This is, in our opinion, relatedness. Depending on the textual context taken into account, we can further distinguish:

    - **Local syntagmatic relation**: collocations are one example, e.g. "good appetite", or the relation between verb and argument, as in "eat the ham". In these cases both terms are, generally speaking, close in textual context, and a direct syntactic relation is set between them.

    - **Global syntagmatic relation**: related words do not have to appear close to each other or in the same sentence. Here we find topic-related relations, e.g. the one existing between words referred to cookery, such as ham, stew, fork, kitchen, etc. We can say that the topic puts them into relation.

      In some cases, two words do not need to appear in the same textual context, but in contexts that share similar features, either syntactic or semantic. Therefore, if two words turn up in two similar texts, we can establish that there is an **indirect global syntagmatic relation** between them.

Even if this distinction may seem rather fuzzy, we will soon show that most of the studied systems fit clearly in one of these classes.

Another difference has to be set between word relatedness and concept relatedness. We are more interested in the second one, that is, in conceptual rather than linguistic relations. In order to see the relevance of concepts, Hirst (1987:5) states: "*Any practical NLU system must be able to disambiguate words with multiple meanings, and the method used to do this must necessarily work with the methods of semantic interpretation and knowledge representation used in the system*". Ontologies, Lexical Knowledge Bases (LKB) and Dictionary Knowledge Bases (DKB) are also usually organized according to concepts, as in WordNet: "*The most ambitious feature of WordNet, however, is its attempt to organize lexical information in terms of word meanings, rather than word forms*" (Miller et al., 1993b:3). There are some exceptions in DKB and LKBs, as some systems are unable to do sense disambiguation, but they admit the necessity of arranging the knowledge base according to concepts. For instance Richardson (1997:113) reports: "*In the future, this approach may be much more viable with a sense disambiguated LKB, which is work currently in progress.*"

Both word relatedness and concept relatedness are closely linked. Words, being linguistically similar, are also conceptually alike in one or more meanings, and, vice versa, words serving to name two similar concepts are also similar.

Taking into account all we have considered until now, we will study the relatedness measures in accordance with six features:

- Regarding the used resource: dictionary, ontology, corpus or a combination.
- Paradigmatic or (global/local) syntagmatic relatedness.
- Relatedness between either words or concepts.
- Evaluated on wide texts, just a few words, or not evaluated at all.
- Evaluated with nouns only, or with all parts of speech.
- Precision of the results: no results reported, medium, good, or excellent results.

As stated previously, the evaluation of relatedness is not easy. It is sometimes carried out with the help of ad hoc lists of related words elaborated by people, but more often the evaluation is done indirectly, taking into consideration the results obtained from applications such as word sense disambiguation, information retrieval or other ones. The problems of the former approach are that the lists produced by different researchers do no agree, as well as the lack of guidelines to construct such lists. Furthermore, when comparing the score produced by the system with that of the human-produced lists, only perfect matches are counted, even if the words that do not match are closely related.

We will now focus on the relatedness antecedents, paying special attention to the features named before, which are summarized in a single line after the exposition of each system.

VI.A.1. Antecedents based on ontologies

If ontology (see chapter V for our definition of ontology) is taken as basis, relatedness of two objects can be deducted from the information in the ontology. Tversky (1977), in the first axiomatization of similarity which came from the field of psychology, said: "*A new set-theoretical approach to similarity is developed in which objects are represented as collections of features, and similarity is described as a feature-matching process*". Therefore, he used a representation model based on features. Its measure was applied to different tasks, e.g. similarity of characters, of faces and of nations. In its evaluation, he compared his axiomatizing with people's intuition on similarity.

At that time in Artificial Intelligence, semantic networks were the most usual representation models, and similarity was developed mainly using *spreading activation* techniques on such networks (Quillian, 1968; Collins & Loftus, 1975). As for Collins and Loftus "*The conceptual network is organized along the lines of semantic similarity. The more properties two concepts have in common, the more links there are between the two nodes via these properties and the more closely related are the concepts*"[10]. They did not directly implement their model, but claimed that it followed the results of psycholinguistic experiments.

So as to make the *spreading activation* implementation easier, Rada et al. (1989) made quite a lot of work around the evaluation and merging of semantic networks. The measure of relatedness they present is named Semantic Distance: "*… [in spreading activation] semantic relatedness is based on an aggregate of the interconnections between the concepts. This is different from semantic distance which is equal to the minimal path length between two concepts*". Moreover, considering that there is a privileged relation structuring the semantic networks –the class-subclass or is-a relation–, instead of using all relations they claim that it is enough to apply the is-a relation: "*we hypothesize that […] is strong enough for the length of is-a paths to be used as a measure of semantic relatedness*". In their proposal for the distance formula (cf. 1st equation), distance between the concepts A and B is defined as the length of the shortest path of is-a[11] relations that links both concepts.

$$\mathrm{dist}(A,B) = \min_{p \in \mathrm{path}(A,B)} \mathrm{length}(p) \qquad (1)$$

The distance measure would be small for two closely-related concepts, and vice versa. No evaluation report was presented. This formula, in its simplicity, is quite often used, e.g. to merge different ontologies (Khnigt & Luk, 1994; Utiyama & Hasida, 1997).

[12]Ontology/paradigmatic/concepts/few/words/no results

Sussna (1993) developed further Rada´s idea applying it to the WordNet knowledge base, in order to perform word sense disambiguation on a document indexing application. The concepts of the knowledge base are word senses in this case, and, apart from subclass relations, he also proposes to use all the other relations in WordNet. Each relation will have a similarity weight (see $w_r(x,y)$ in the 2nd equation[13]) as, for example, concepts linked by a synonymy-relation are more similar than those linked by part-of relations (see also Tversky, 1977). The distance between two adjacent concepts in

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[10] As we can see similarity and relatedness are confused in this work as well.

[11] As it is not necessary for this dissertation, we will not differentiate between class-subclass and is-a relations.

[12] These are the values for the features we have mentioned above, regarding the work of Rada et al.

[13] w_r in Sussna´s work is more complex than stated here, but, as he says "*the particular weights used* [w_r] *may not make that much difference*".

the semantic network (*w*(*x,y*) in the 2nd equation) is defined as the addition of the weights of all the relations between both concepts. In addition, the deeper the concepts are in the hierarchy, the shorter would be the distance (as captured by the divisor *d* in the equation).

$$w(x, y) = \sum_{r \in Wordnet-relation} \frac{w_r(x, y)}{d} \tag{2}$$

Therefore, the path having the smallest weight (cf. 3rd equation) will yield the distance between any two concepts.

$$\begin{aligned} &\text{dist}(x, y) = \min_{(x, x_1, \ldots, x_n, y) \in \text{path}(x, y)} \sum_{i=0}^{n} w(x_i, x_{i+1}) \\ &\text{where } x = x_0 \text{ and } y = x_{n+1} \end{aligned} \tag{3}$$

Sussna does not do a direct evaluation, but an indirect one, through the results obtained on a word sense disambiguation task.

Ontology/paradigmatic/concepts/wide/nouns/good results

Mahesh et al. (1996; 1997) take the richness of the Microcosmos ontology as starting point, and argue that *spreading activation* performs word sense disambiguation in a blind way: " … *spreading activation … does not make use of available knowledge*." When searching the paths between word senses, they affirm that the argument structure taken from the semantic analysis of the sentence should be considered. In other words, relatedness would measure the degree to which the selectional restrictions of verbs or adjectives hold for the chosen word senses. In order to compute this, they use concept-based selectional restrictions and the hierarchy of concepts.

Ontology/ paradigmatic and local syntagmatic/concepts/proposal/nouns-verbs/no results

VI.A.2. Measures based on Electronic Dictionaries

There are no concepts in dictionaries, but word senses. However, these respond to conceptualizations made by lexicographers, and, in a big sense can be compared to ontology concepts. How can relatedness between those senses be measured? Unlike ontology-based works, there is no formalization based on psychology or knowledge, but only on practical approaches.

Regarding the type of relatedness, it can be said that indirect global syntagmatic relations are broadly used. In order to see whether two senses are related, their context is checked (as we are using dictionaries, the context is the definition of the sense). If they are similar, then the senses are taken to be related. The hypothesis sets that related senses will be defined with related words.

Lesk (1986) applied this hypothesis directly to word sense disambiguation: the relatedness measure of two senses is the amount of words shared by the corresponding definitions. The more words appear in both definitions, the more closely related both senses would be. As we will see below, his intuition has been fruitful, but it is also very weak, as it is subordinated to the actual words chosen when writing the definition. The evaluation is carried out through a sense-disambiguation task. The same method is put forward in (Cowie et al., 1992; Wilks et al., 1996), but in order to improve the efficiency when measuring the relatedness of a set of words, they use an optimization technique known as *simulated annealing*.

Dictionary/global syntagmatic/concepts/wide/ nouns/medium results

Veronis and Ide (1990) hold the same approach, but go further following a circular definition: the relatedness measure of two senses will be given by means of the addition of the relatedness measure of the words used in the definitions. In other words, now it is not necessary that the same words appear in the definition of both senses, it is enough if related words are used. And, when are two words related? When their senses are related. In order to see whether this hypothesis is useful or not, they built up a huge neural network using the terms appearing in dictionary definitions, adding links between the *definiendum* and the words in the definition[14], and tested it in a sense-disambiguation task (there is no systematic evaluation). The same approach was taken by Kozima and Furugori (1993), but with the object of improving efficiency, they compile the information into a vector-model (Kozima & Ito, 1995), similar to the model presented below –see also (Niwa & Nitta, 1994)–. They evaluate comparing similarity lists built up from people's intuition.

Dictionary/global syntagmatic/words/few/nouns/no results

Lesk´s method followed another development, which used vector-models based on co-occurrences in dictionary definitions. Wilks et al. (1990; 1996) collected word co-occurrences from the definitions of LDOCE. As definitions in LDOCE have been written using a reduced vocabulary (comprising 2781 words), co-occurrences are limited to those terms. As laid down by the authors, two words co-occur when they appear in the same definition. For codifying the co-occurrences of each word, they use a vector (see 4[th] formula). In this vector, there will be a value for each word in the reduced vocabulary (N in the 4[th] equation equals to the size of the reduced vocabulary, 2781), representing the co-occurrence strength for the word w and the i-th word in the

[14] Definitions were not lemmatized, nor analyzed.

reduced vocabulary. Six different formulas are put forward to measure the strength, all of them based on frequencies of words and co-occurrences. In the 5th equation, for example, the vector values are just the gross frequencies of the co-occurrences.

$$\vec{v}_w = \left(v_0^w, \cdots, v_N^w\right) \tag{4}$$

$$v_i^w = f_{w,z_i} \tag{5}$$

As to estimate the relatedness between two words, we can mathematically calculate the relation between the two corresponding vectors, using, for example, the cosine (see equation 6), but the authors also propose other three formulas. Wilks et al. go further on, getting the relatedness measure for word senses by creating a vector for each dictionary sense, summing up all the vectors for the words in their definition (cf. 7th equation). In this way, the mathematical measure of the relation between two vectors will yield the relatedness measure for two senses (it is enough to replace words for word senses in *w* and *z* of equation 6, using the vectors from equation 7).

$$\mathrm{sim}(w,z) = \cos(\vec{v}_w, \vec{v}_z) = \frac{\sum_{k=1}^{N} (v_k^a v_k^b)}{\sqrt{\sum_{k=1}^{N} v_k^a \sum_{k=1}^{N} v_k^b}} \tag{6}$$

$$\vec{v}_a = \sum_{w \in \mathrm{def}(a)} \vec{v}_w \tag{7}$$

This method, instead of measuring directly the overlap of words in definitions, uses the vectors for those words. The evaluation is not very thorough, as they carried out the sense-disambiguation of occurrences of *bank*.

Dictionary/global syntagmatic/concepts/few/nouns/good results

Richardson´s approach (1997) is quite alike to the ontology-based ones. In fact he builds up a semantic network from the definitions of two dictionaries (*LDOCE* and *Webster's 7th* Gove, 1969), after syntactically analyzing the definitions and extracting semantic relations. Each semantic relation has a weight based on frequencies. As the words in the definitions are not sense-disambiguated in this semantic network, it is not possible to measure the relatedness between two senses. Instead, it implements relatedness among words using paths of relations. The idea is similar to the *spreading activation* method: two words will be closely related if there are many relation-paths between them.

All relation-paths are not equally meaningful, and he is, therefore, in need of measuring the contribution of each type of relation. In order to weight each kind of relation, he uses an empirical method, which compiles 50.000 pairs of closely related words from a thesaurus and 50.000 pairs of non-related words. Sense ambiguity can cause errors in the paths joining two words (if a word in the path had different senses in each definition it appeared), so he is forced to apply very short paths, no longer than two definition words. The evaluation is made through the utilization of this thesaurus, applying held-out pairs not used for calculating the weights.

Dictionary/ paradigmatic and global syntagmatic/ words/ wide/ nouns/ good results

VI.A.3. Alternatives based on corpora

Researchers that advocate the use of corpora quote Firth (1957) often: "*you shall know a word for the company it keeps*". In other words, the features and meaning of a word will be given by the context where it appears, or, better, by the analysis of all the contexts the word appears in. On this basis, the following hypothesis has been set: Two words will be closely related if they come up in similar contexts. In order to analyze the relatedness between words, we only need to compare the contexts where they appear. Whether global or local syntagmatic relatedness is defined depends on the particular features used to model the context. If we want to study local syntagmatic relatedness, words with a direct syntactic relation will be used. In the case of global syntagmatic relatedness, wide windows are used (about ±50 words) without taking into account the order and using content words only.

So as to be able to develop corpus-based techniques that measure the relatedness between senses, the words in the corpus have to be labeled with senses, forming a training-corpus. This is one of the problems of corpus-based techniques, the need of extensive manual sense-disambiguation.

Mutual Information (MI) has been a simple and successful measure (Church & Hanks, 1990; Gale et al. 1992; 1993), which is founded on information theory. According to mutual information, if two words tend to appear always together in context, their relatedness would be stronger. On the contrary, if two terms never appear in the same context, their relatedness would be weaker. Church and Hanks use 100 word windows as context. In order to calculate the MI of words *v* and *w*, we have to consider the probabilities of each word and of both words appearing together (cf. 8th equation).

$$\mathrm{MI}(v,w) = \log \frac{\Pr(v,w)}{\Pr(v)\Pr(w)} \tag{8}$$

The easiest way to estimate these probabilities –called *maximum likelihood estimate*– is to take the counts of each word (cf. f in equation 9) and divide it by the total quantity of words N.

$$\Pr(x) \cong \frac{f_x}{N} \tag{9}$$

Corpus/global syntagmatic/words[15]*/few/nouns/good results/sparse data problem*[16]

MI is used in many applications, and the most quoted problem in literature is the estimation of the probabilities for rare events. All statistical techniques have also to face this problem, because a few words appear very often in texts, but most of them do it very rarely (in accordance with Zipf´s law). This problem is known as the *sparse data problem*. Which is the probability of occurrence for a word never seen in the corpus? And which is the probability of co-occurrence for two words that have turn out twice in the corpus but not together? It would be unfair to assign these two events 0 probability. The techniques brought into service to face this problem are called *smoothing* techniques.

Schütze (1992a; 1992b; 1998) found another alternative to the word co-occurrence method. He coded co-occurrences with vectors and measured the relatedness between words by means of the angle between the vectors (see Wilks´ method in the previous section). In order to be able to extend relatedness to word senses, he groups automatically the contexts of a word, by summing the vectors for all the words in the context and using clustering techniques. A human expert can then analyze the resulting clusters for each word, and assign a word sense to each cluster. According to the authors, this would be easier than tagging each occurrence of the word in the whole corpus one by one.

Corpus/global and local syntagmatic/words/wide/nouns/good results/no sparse data problems

From all the information in texts, MI and the vectors of Schütze only take into account the co-occurrences of words. There is doubtless more richness, e.g. syntactic structure. The syntactic structure can be reflected using very simple schemes, as part of speech labels appearing close to the target word, but argument structures (verb-object, noun-adjective, etc.) have also been used. Syntactic structure is usually represented as features, and therefore, the syntactic context of a word is expressed by syntactic features extracted from the corpus (that is, part-of-speech or argument structures found for the occurrences of the word). If the corpus is tagged with word senses, the

[15] We classify it as relatedness between words, because it is not straightforward to extend it for senses, as it would need hand-tagging.

[16] According to the relevance in corpus-based alternatives, we have added the sparse data problem as another feature.

relevant syntactic features for each sense can be thus collected, being directly used in sense-disambiguation (cf. chapter IV). So as to formalize relatedness, syntactic features must be used indirectly: words appearing in contexts with similar syntactic features would be closely related (in fact, we classify these relatedness measures as indirect global syntagmatic). That is what Grefenstette does (1992; 1996) when he defines the relatedness measure between words based on syntactic features. He makes an interesting evaluation, similar to that of Richardson, taking a thesaurus as a standard for measuring relatedness.

Corpus/global syntagmatic/words/few/ nouns/good results/sparse data problem

In some works a specific syntactic relations is used. For instance, many of the studies on the selectional restrictions of verbs (Grishman and Sterling, 1994; Lee, 1997) extract verb-object or verb-subject pairs form corpora, and try to find the class of nouns fitting best in each argument of the verb. By doing these, they define a measure of relatedness between verbs and nouns.

Corpus/global syntagmatic/words/few/nouns/good results/sparse data problem

VI.A.4. Combinations between ontologies, dictionaries and corpora

There are quite a few works advising the improvement of previous approaches. The reasons are various. Most important, all techniques above see the lexicon as a list without any semantic structure. Words and concepts are organized around classes, and lots of semantic features of a word are really features of the class. Therefore, why should we keep the information for each word, if most of it can be generalized as class features? Besides, the main problems of the statistical approach (**sparse data problem** and **the need of hand-disambiguation**) would be reduced if words were organized around classes. For example, in order to define the most typical object of the verb "to eat", it is much better to use the class *eatable-object*, rather than listing *sandwich*, *ham*, *hake, apple*, etc exhaustively. Moreover, although *kiwi* does not appear in the corpus as an object of *eat*, if it is classified as an *eatable-object*, we will be able to infer the relation between *kiwi* and *eat*.

Some works try to induce classes from the corpus itself (for example, in the above mentioned Schütze´s work), but, it usually introduces a considerable degree of noise. Other works propose to use thesaurus or ontologies, in the search of intuitive and straightforward class definitions. Yarowsky (1992), for instance, in a work on sense-disambiguation takes as classes the ones given by Roget's thesaurus. In Roget's thesaurus (Kirkpatrick, 1987) each conceptual category is made of a list of related words. In order to know which are the typical contexts for each category, he collects contexts for each word in the category from the Grolier encyclopedia. Each context is made by the

100 surrounding words. He then selects from all the words in the context of the category, the most significant[17] ones, according to a statistical measure called *saliency* (see equation10).

$$\text{saliency}(w) = \log \frac{\Pr(w \mid c)}{\Pr(w)} \tag{10}$$

In this work relatedness of words is not explicitly defined, but it is implicitly used as a method to label words with Roget´s class. Nevertheless, as in many works related to corpora, it is possible to infer the relatedness between words or senses from the measures given. Another example of this combined approach takes a similar measure trying to extract information for ontologies (Basili et al. 1997; 1995; Cucchiarelli & Velardi 1997).

Ontology+corpus/global syntagmatic/concepts/wide/nouns/very good results/no sparse data problems

Resnik (1993a; 1993b; 1995; 1997) proposes a different strategy to combine the information of ontology and corpus. As to measure the relatedness between two word senses, he first looks for their closest common ancestor in the hierarchy of the ontology (WordNet). Instead of measuring the distance to this common ancestor, he estimates the information content of the class represented by it and uses this as the relatedness measure (see formula 11, where v and w are nouns, and c the closest common ancestor).

$$\text{similarity}(v, w) = -\log \Pr(c) \tag{11}$$

Class probabilities can be estimated using the frequencies in the corpus that the words belonging to the class have:

$$\Pr(c) \cong \frac{\sum_{w \in c} f_w}{N} \tag{12}$$

[17] As for Yarowsky "*words that are likely to cooccur with the members of the category*".

This relatedness measure has been used to calculate the strength of the relation between noun senses and verbs, so as to induce selectional restrictions for verbs. It has also been used to perform word sense disambiguation of nouns, achieving good results in both tasks. Li and Abe (1995; 1996) also apply this approach in the induction of selectional restrictions and automatic clustering of nouns.

Ontology+corpus/paradigmatic/concepts/few/nouns/good results/no sparse data problems

Hearst and Schütze (1993) combine the relatedness measure for words introduced in Schütze´s previous work (1992a; 1992b) with the hierarchical information of WordNet. Their main target is to relate concepts that have no relation in WordNet's hierarchy. For instance *ball* and *referee* are closely related, but very loosely related in WordNet. They first group all synsets in WordNet in 726 categories, according to their position in the hierarchies. Then they use techniques similar to Schütze's to find relations among these groups. There is no systematic evaluation of results, and the authors themselves have confessed having obtained few relations. On the other hand they do not propose any new relatedness measure based on the so-built concept network.

Ontology+corpus/global and local syntagmatic/concepts/few/nouns/good results/no sparse data problems

Karov and Edelamnn (1996; 1998) count on dictionaries in order to collect the preliminary contexts (sentences in this case) that are related to a given word sense, avoiding in this way the need of hand-tagged data. They think there is a circularity in relatedness: words are related if they appear in similar sentences, and sentences are related if they contain related words. So as to break this circularity they take an iterative algorithm which reaches convergence and yields as result a relatedness measure for word senses and a set of sentences automatically tagged with word senses. The main advantage of their approach is the ability to train on fewer data.

Dictionary+corpus/global syntagmatic/concepts/few/nouns/good results/no sparse data problem

VI.B. Conceptual Density

In this section we introduce our proposal for the formalization of ontology-based relatedness. We want this formalization to meet the following conditions:

1. It is based on ontologies.
2. It measures relatedness among senses, making reference to ontology concepts.
3. It uses information from paradigmatic and syntagmatic relations.
4. It works for all open-class words[18].

[18] Mainly nouns, verbs and adjectives.

5. It is efficient, so as to be able to work with long texts.

The first two conditions are related, since ontologies involve relations between concepts. There, ontology should include paradigmatic and syntagmatic relations, so that we have as much information as possible when deciding the relatedness degree. The other advantage of ontologies is that there is no need to care for learning, that is, there is no need of previous hand-disambiguation. Finally, it has to be useful to work with adjectives, nouns and verbs, and efficient enough to work with real texts, not just with a few specific words.

VI.B.1. Two concepts: distance

We have taken as a starting point Rada´s work (Rada et al., 1989) and specially Sussna´s work (1993). As laid down in their research, relatedness can be formalized by means of the Conceptual Distance[19] between ontology concepts[20]. According to Sussna, there are two factors that have to be taken into account when calculating Conceptual Distance: the length of the relation-path between two concepts (the longer the path is, so is the distance) and the depth of the concepts (the deeper the concepts are, the shorter the distance is). Therefore we proposed the following formula in (Agirre et al, 1994c):

$$\begin{aligned}&\mathrm{Dist}(a,b) = \min_{p\in \mathrm{path}(a,b)} \sum_{c_i \in p} \frac{1}{\mathrm{depth}(c_i)} \\ &\text{where } a = c_0 \text{ and } b = c_n\end{aligned} \qquad (13)$$

Conceptual Distance between two concepts (*a* and *b* in the 13th equation) is given by the shortest path (*p*), as long as we calculate the length in a special way: for each concept in the path we will add the inverse of its depth in the hierarchy (for more information, see Agirre et al. 1994c).

VI.B.2. N concepts: density

Conceptual distance, as it stands, might be useful in many applications, but if we want to generalize distance between two concepts to distance among N concepts there is a combinatorial explosion. Using pairwise distance it is possible to measure the distance of N concepts by adding up the distance for all possible pairs (see Sussna, 1993). In order to compute the distance among eight

[19] At the beginning of this chapter, when defining relatedness, we have mentioned semantic distance. As semantic distance is not formalized and we have joined it to an ontology, we therefore call it conceptual distance.

[20] Relatedness and Conceptual Distance are opposed: the conceptual distance of two closely related concepts is close to zero, and the conceptual distance between two non-related concepts tends to ∞-.

concepts, for example, we will have to examine every pairwise combination[21] of eight, that is, twenty eight pairs. When computing the distance among all the nouns of a sentence, things get more difficult, because of word sense ambiguity. Let's assume that a given sentence has 8 words, and each word has 3 word senses. If we wanted to calculate the distance of all pairwise word sense combinations, we would have to try all word pairs (28 as before) for each possible sense combination (3^2): in total 252. Generally, if there are N words, having M senses each, we will have to measure the distance between two concepts $\binom{N}{2} \times M^2 = \frac{N \times (N-1)}{2} \times M^2$ times.

Besides, the comparison between concept sets gets difficult. Consider two sets of concepts, A and B, with a pair of concepts in each. For A and B it is possible to say that the two concepts in A are closer than the ones in B: we just have to compare the distance for each pair. If we add another concept to A, the distance among the three concepts will get bigger, and it will be impossible to compare the distance for this new A with the distance for B, because we are measuring distances among different quantities of concepts.

For this reason, we will add the following conditions to our measure:

6. The measure works for any number of concepts.
7. The measures for sets with different number of concepts are comparable.

Back to our first condition, we have to choose an ontology in order to apply the measure. Unfortunately, there are few ontologies which are nowadays both wide and free, being WordNet the only one with a good coverage vocabulary and freely accessible (see comments about this choice in section V.D). WordNet has been constructed with nearly no syntagmatic relations, having this an effect on one of the conditions, namely, that of using paradigmatic and syntagmatic relations. Therefore we have to alter conditions one and three:

1. It is based on the WordNet ontology.
3. It uses information from paradigmatic relations.

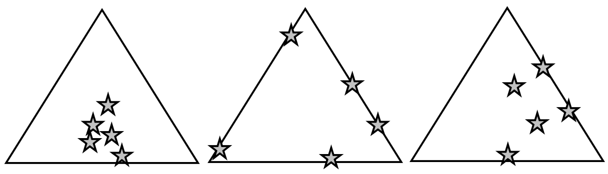
According to some authors, the fact that we stick to paradigmatic relations only is not such a hard constraint: "*we hypothesize that … is strong enough for the length of is-a paths to be used as a measure of semantic*

[21] $\binom{8}{2} = \frac{8 \times 7}{2} = 28$

relatedness" (Rada et al., 1989). The application of just hierarchy relations, in addition, has allowed us to attain a substantial improvement in efficiency, as we will see.

A measure for N concepts is not such a natural thing to develop. Up to now it was very clear that the grounds of our formulation were both the length of the path between two concepts, and the depth of the concepts in the path. However, the measure of N concepts has to look for another foundation: the abstraction to have in mind will be that of density instead of distance, that is, the amount of concepts in the subtrees of the hierarchy rather than path-length. Before going any further, we will lay some terminology. In order to differentiate them from the other concepts in the subtree, the concepts for which we are actually measuring the relatedness will be called **traces**.

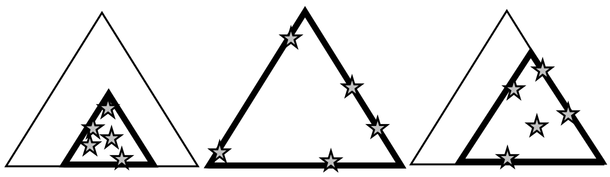
The key idea for this measure comes from the answer to this question: how many traces are needed in a subtree of the hierarchy, so as to say that the subtree is full up with traces? Or, in other words, when comparing two subtrees, how can we measure which one is fuller?



1st figure: the same subtree with three different sets of traces.

In figure 1 the same portion of the ontology appears three times, each time with a different set of traces. Would we say that the traces are equally close in the three settings? No. It seems that relatedness should be higher for the subtree on the left side, lower for the one on the middle and somewhere in between for the one on the right side. Talking about density, the highest density would be for the leftmost subtree and the lowest for the middle one. If we used Conceptual Distance of concept pairs, we would get the same result, that is, the paths between traces would be short in the leftmost subtree, and long for the traces in the middle subtree.

Leaving path lengths aside, we can observe that one of the distinguishing feature for the three sets of traces is the minimum subtree covering all five traces, as shown in the 2nd figure.



2nd figure: minimum sub-trees covering the trace sets
(shown with bolder line).

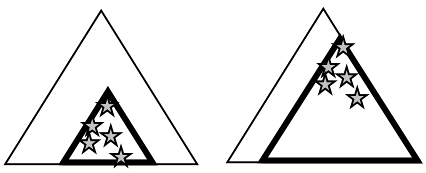
Taking in mind these sub-trees it is quite easy to see that there is a relation between relatedness among traces and the size of the minimum subtree[22]: the subtree with the highest density has the smallest size (left), and the one with lowest density the biggest size (middle). We can thus conclude that what we call density should be the relation between the amount of traces and the size of the minimum subtree covering all traces. This relation could be expressed, for example, by the amount of traces (see *a* in equation 14) divided by the size of the subtree (area(*Z*)) covering all traces (*Z* in equation 14).

$$\text{density}(Z, a) = \frac{a}{\text{area}(Z)} \tag{14}$$

Equation 14, in a first approach to density, yields the density for the subtree *Z* covering *a* traces. And, which will the density for a set of traces be? It will be given by the density of the minimum subtree covering the whole trace set *A*, or, in other words, the density of the subtree covering the trace set *A* that obtains the maximum density, as shown in equation 5[23].

$$\text{density}(A) = \max_{Z,\ \text{where}\ Z \cap A = A} \text{density}(Z, |A|) \tag{15}$$

Back to density as defined in equation 14, it takes into account the main features of Conceptual Distance: closeness and depth. The closer traces are, the smaller the area of the subclass covering the traces is (see figure 2). The same stands for depth: the deeper the traces are, the smaller the subtree is. This is shown in figure 3, where we have two sets of traces that are equally compact, but the set on the left is deeper. The set on the left will get higher density, following equations 15 and 14, because the area of the minimum subtree is smaller for the leftmost set of traces.



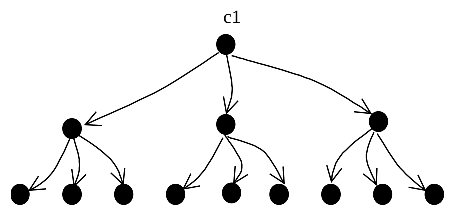
3rd figure: minimum subtrees (shown with bolder lines) covering two sets of equally compact traces.

[22] Size, area and number of nodes are equivalent ways of referring to the same measure.

[23] So as to say that subtree *Z* covers the set of traces *A*, we use $A \cap Z = A$. In order to express the amount of traces in *A*, we use its cardinal $|A|$.

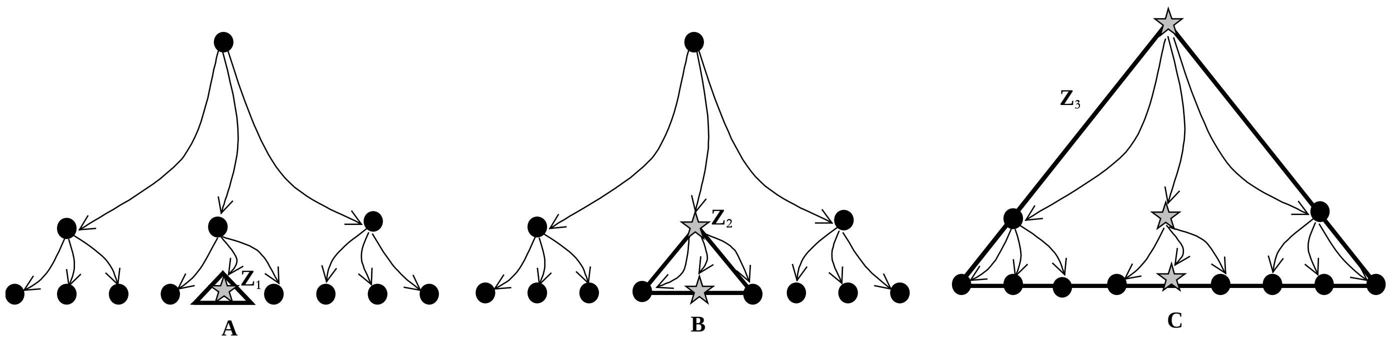
The measure defined in the 14th equation, however, has quite a lot of problems. Before analyzing them, we need to define some measures about tree topology and the relation among them: <u>the height of a subtree</u> (h_Z), <u>the average number of children</u> for the concepts in the subtree (μ_Z, also called branching-factor), and <u>the area of the subtree</u> (or size of the subtree, given by the amount of concepts in the subtree). The relation among these three measures –area or number of concepts, height and average number of children– is given by equation 16. An example of these measures is shown in figure 4, by means of some regular subtrees.

$$\text{area}(Z) = \text{number\_of\_concepts}(Z) = \sum_{i=0}^{h_Z-1} (\mu_Z)^i \qquad (16)$$



4th figure: the height for the subtree rooted in concept c1 (3), the average number of children of the concepts in the subtree (3), and area or number of concepts ($13=3^0+3^1+3^2$).

The problems of the 14th equation arise from the 7th condition, due to the need to compare the densities of sets with different number of concepts. Let's suppose that we want to measure the density of three different concept sets (A, B and C): one has a single trace, the other one two, and the last one three, as shown in figure 5. The subtree covering each trace is displayed with a triangle.



5th figure: three trace sets in the same subtree. Concepts are drawn as ● and traces as ☆.

According to our intuition on relatedness, would we say that the two traces in set B are more related than the three traces in set C? Or should both groups have the same relatedness? In the relatedness measure we want to formalize, we want to state that concepts from sets B and C have the same relatedness. The 14th equation, on the contrary, indicates us something different:

density(A) = density(Z_1,1) = 1/1 = 1

density(B) = density(Z_2,2) = 2/4 = 0,5

density(C) = density(Z_3,3) = 3/13 = 0,23

In our opinion, the density of all these trace sets should be 1, and to obtain this we have better not to count the traces, but to use another reference: the relation between the area and the amount of traces is not enough, and we need to consider also the height.. For instance, in figure 5, the height of subtree Z_1 is 1 and it contains one trace; the height of Z_2 is 2 and it contains 2 traces; and the height of Z_3 is 3 and it contains 3 traces; in all three the average number of children is the same.

From another point of view, what kind of weight should be given to each trace in order to make density of the trace sets in figure 5 equal to 1? Before answering this question, we will rewrite equation 14, replacing the area with the formula in equation 16, leaving a yet unknown function of the number of traces in the dividend (cf. equation 17).

$$\text{density}(Z,a) = \frac{\text{f}(a)}{\text{area}(Z)} = \frac{\text{f}(a)}{\sum_{i=0}^{h_Z-1}(\mu_Z)^i} \tag{17}$$

Let us assume that we want to obtain the same density for all three trace sets in figure 5, and we want to make their density equal to 1. The relation we are seeking has to be established between the height and the amount of traces. As the height appears in the summatory of the divisor in equation 17, we will set f(*a*) as the formula in the dividend, but replacing the height of the tree with the number of traces *a* (cf. equation 18).

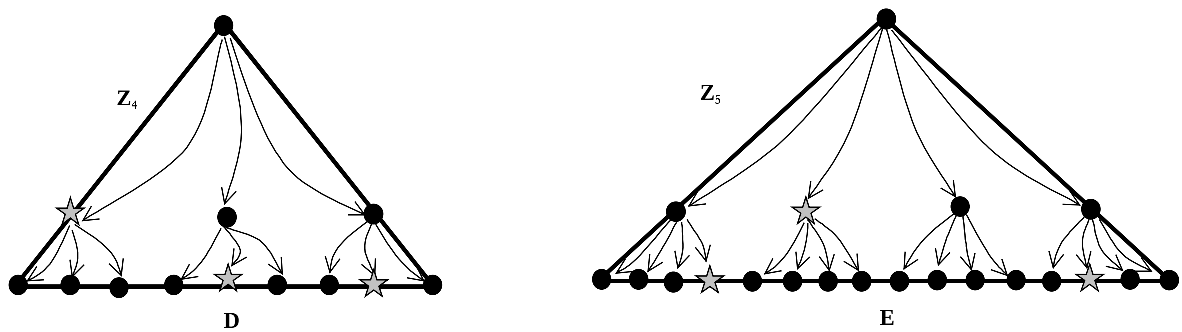
$$\text{density}(Z,a) = \frac{\sum_{i=0}^{a-1}(\mu_Z)^i}{\sum_{i=0}^{h_Z-1}(\mu_Z)^i} = \frac{\sum_{i=0}^{a-1}(\mu_Z)^i}{\text{area}(Z)} \tag{18}$$

The divisor of the 18th equation shows the area of the subtree. The dividend shows the area that a regular subtree with the same average number of children and covering *a* traces should have in order for its density to be 1. In other words, the dividend represents a regular tree with an average number of children μ_Z that has a density of 1, and whose height equals the number of traces covered. This formula captures the relation between number of traces and area of the subtree.

The 14th equation presents yet another problem when comparing sets of traces, which is related to the topology of the subtress. As it is well known, different parts of ontologies usually have differing topologies, for example, some parts are rich in concepts, and other ones are poor. In the concept-rich parts, the average number children is bigger, being the opposite in the concept-poor parts. Let us assume that we have two concept sets located in different areas of the ontology, both with 3 traces (sets D and E in figure 6). Traces in D and E have the same distance, but, following equation 14, the densities are different:

density(D) = density(Z_4,3) = 3/13 = 0,23

density(E) = density(Z_5,3) = 3/21 = 0,14



6th figure: two different subtrees with a density of 1.

Using equation 18, however, the densities for all the trace sets considered is 1, as we wanted[24]:

density(A)=density(Z_1,1) = 1/1 = 1

density(B)=density(Z_2,2) = (1+3)/4 = 1

density(C)=density(Z_3,3) = (1+3+9)/13 = 1

density(D)=density(Z_4,3) = (1+3+9)/13 = 1

density(E)=density(Z_5,3) = (1+4+16)/21 = 1

[24] Take into account that for all subtrees, μ_Z is 3, except for Z_5, where μ_Z is 4.

In the present dissertation, therefore, Conceptual Density of concepts will be defined by means of the 15th and 18th equations.

VI.C. Implementation

Conceptual Density was implemented using the hypernymy relation in WordNet. Conceptual Distance has been implemented not only for WordNet, but also for the LPPL Dictionary Knowledge Base (Agirre et al., 1994b; 1994d). In the present dissertation we only make use of Conceptual Density, and we will not therefore define the implementation of Conceptual Distance. Before presenting the implementation we will first study some variants of Density.

VI.C.1. Variants of Conceptual Density

During the implementation we have considered that it would be interesting to study several variants and parameters of Conceptual Density. It is difficult to decide *a priori* which of the possible settings is the most convenient, and therefore, we have adopted an empirical approach, using a practical application as test-bed. The chosen application is word sense disambiguation. In this chapter the variants and parameters are introduced, but the experimental results will be shown in chapter IV (cf. Agirre & Rigau, 1996a).

VI.C.1.a) Parameter α

The formula of Conceptual Density gets in trouble when the number of traces under a subtree is too big, as the divisor in the 18th equation grows exponentially. In order to reduce this effect we added a parameter (α) to the formula, for which we found an optimal value empirically. The parameterized formula is displayed in the 19th equation.

$$\text{density}(Z, a) = \frac{\sum_{i=0}^{a-1} (\mu_Z)^{i^{\alpha}}}{\text{area}(Z)} \qquad (19)$$

VI.C.1.b) How to calculate μ: μ_Z and μ_{WN}

When calculating Conceptual Density it is important to take into account the topology of the tree, which we reflect using μ_Z, the average number of children. As it can be expensive to compute μ_Z at execution time, it seems convenient to have it pre-computed and stored for each subtree in the ontology. Furthermore, we can also store the area of each subtree. When calculating density it would suffice to retrieve the area and value of μ_Z for the subtrees under consideration.

We have already studied (see equation 16) the relation among the average number of children in a subtree (μ_Z), the height of the subtree (h_Z) and the area (*area(Z),* number of nodes). Figure 7 shows the linear-programming algorithm in pseudocode, which given the height (H) and area (A) yields the average number of children (μ). The desired precision for the result is given as a parameter (d).

```
Input:        H height, A area
Output:       μ average number of children
Parameter:    d precision
Precondition: A>H

   if 1 <= A < H
      then μ := 1 - 1/a
      else μ := a^(1/n)
   endif
   loop
      s := μ^n;
      e := (μ*(s-A) + A - 1)/(H*s - A);
      μ := μ - e;
   until |e/μ| < d endloop
```

7th figure: algorithm for computing μ_Z

On the other hand, instead of the local measure μ_Z, we can use the global average number of children of the whole WordNet ontology (μ_{WN}). In this case we do not need to compute μ_Z for all the subtrees, but a worse measure of density is expected. In order to check whether this is the case we carried out several experiments, as reported in chapter VII (cf. Agirre & Rigau, 1996a).

VI.C.1.c) Other relations in WordNet: meronimy

Conceptual Density uses only hypernymy. However, there is another hierarchic relation among nouns in WordNet: meronymy (cf. chapter V.D). In principle, the more types of relation we consider the better results we can expect. We have empirically studied whether using meronimy improves the results or not (see chapter IV and Agirre & Rigau, 1996a). Concerning the implementation, when calculating the area of a subtree or when deciding whether a sense is covered by a subtree, meronym relations were treated as hypernym relations. The formula of Conceptual Density did not have to be changed to accommodate meronimy.

VI.C.2. Implementation on WordNet

Conceptual Density on WordNet uses just hierarchic relations, and we therefore designed an efficient algorithm that takes advantage of this.

When measuring density, we are given a set of word senses (AM), which we call traces. First of all we need to build a hierarchy, which is the subset of WordNet covering the given word senses. This subset hierarchy is built following the hypernymy links upward from the traces. All the subtrees to be taken into account will appear in this hierarchy, considering that if a subtree does not have a trace underneath, its density will be 0. Figure 8 shows the algorithm to build the hierarchy. Given a set of word senses (traces), it returns the hierarchy as defined above (H). The data structure for the hierarchy keeps a list of all the nodes in the hierarchy (`H.subtrees` each one representing a subtree) and, for each node, the following information: the list of direct hiponyms (`H[h].hipo`) and the number of traces below the node (`H[h].number_of_traces`), which would be used afterwards to compute density. The algorithm in figure 8 is a simplification, as it assumes that the hierarchy in WordNet follows a tree structure (a single hypernym exists for each word sense). This is not completely true in WordNet, which follows a lattice-like structure. In order to accommodate this, it is enough to change the function `get_hypernymy_chain`, which would return more than one hypernymy chain when the node has more than one parent.

```
FUNCTION: Build_hyerarchy(AM)
   Input:  AM set of traces
   Output: H hierarchy

      for each A in AM do
         hiper_chain := get_hypernymy_chain(A) ;
         hipo := A ;
         for each h in hiper_chain do
            push(hipo,H[h].hipo) ;
            H[h].number_of_traces ++ ;
            push(h,H.subtrees) ;
         endfor
      endfor
      return(H)
```

8th figure: building the hierarchy with the hypernyms of the traces
for which Conceptual Density has to be computed.

The implementation of the 19th equation is shown in figure 9. It computes the density of a subtree that covers a certain number of traces, given the parameter α. The arguments are the subtree itself and the number of traces underneath. It also uses the area of the subtree (`Z.area`) and the average number of children (`Z.μ`), as previously stored (see section VI.C.1.b).

```
FUNCTION:   CD(Z,A)
   Input:     Z  subtree
              A  number of traces
   Output:    CD conceptual density
   Parameter: α
   Data:      Z.area
              Z.μ

      d1 := 0
      i := 0
      while i < A do
         d1 := d1 + Z.μ ^ (i^α)
      end
      CD := d1/Z.area
      return(CD)
```

9th figure: algorythm to calculate Conceptual Distance

Finally, in order to get to compute the Conceptual Density of a given set of traces, following the 15th equation, we will have to compute which subtree from the ones covering these traces has the highest conceptual density. The algorithm in figure 10 applies this method. It returns the density of the subtree with highest density from all the sub-trees covering all traces (`H.subtrees`).

```
FONCTION:   CD(AM)
   Input:   AM set of traces
   Output:  CD Conceptual Density

      CD := 0 ;
      H := build_hierarchy(AM) ;
      for each Z in H.subtrees do
         d := CD(Z,H[Z].number_of_traces) ;
         if d > CD then CD := d ;
      endfor
      return(CD)
```

10th figure: algorithm for the density of a set of word senses

VI.D. Evaluation and comparison with other works

Conceptual Density as defined in the present dissertation (15th and 18th equation) has not been directly evaluated. That is, we have not tested it on a list of related words to check whether our measure of relatedness and human intuition agree, following the reasons shown before (cf. section III.A for evaluation proposals). Evaluation will be carried out according to the applications where density is used, comparing our results with those obtained by other systems (cf. specially chapter VII (Agirre & Rigau, 1996a), but also chapter VIII (Agirre et al., 1998c) and chapter IX (Rigau et al., 1997)).

In this section, we will focus on the analytical comparison of the different relatedness formalizations rather than the evaluation of results. Actually, the main object will be to reason on the following argument:

> *Although the best results are not obtained in some applications, formalizations of relatedness based on ontologies are superior, both from a theoretical perspective and also because of being ready usable for different tasks. In addition, among the formalizations based on ontologies, conceptual density is more general, more efficient and the one achieving the best results.*

We will now discuss separately the two assertions, that is, the advantage of the techniques based on ontologies and the better features of Conceptual Density among ontology-based formalizations. In the following chapter we will use the results obtained on a specific application to compare Conceptual Density with other techniques.

VI.D.1. On the advantage of ontology-based techniques

As seen in the section of antecedents of this chapter, measures based on ontology have their origin in the psychology and artificial intelligence research, and these research works are the only ones studying relatedness in itself, abstracting it from specific applications.

Dictionary measures are quite *ad-hoc* in general. Corpus-based techniques are often used, but dictionary measures have an advantage over them: word senses, concepts, appear explicitly in dictionaries (for headwords generally), and the information given for a word sense can be used to characterize it. That is the foundation for the work of most of the groups: use the information about word senses given by the dictionary (definition, category, domain codes, etc.) to formalize relatedness (Lesk, 1986; Cowie et al., 1992; Wilks et al., 1996; Veronis & Ide, 1990; Kozima & Furugori; Niwa & Nitta, 1994). Karov and Edelmann (1996; 1998) do quite the same as well, but they set up a method to link the corpus and the senses in the dictionary.

We will not say that there is no information about relatedness in the dictionary, on the contrary, but this is raw information, without structure. And that is, indeed, the main contribution of the Microsoft group (Richardson, 1997). They formalize relatedness based on a Dictionary Knowledge Base constructed with relations extracted from the dictionary definitions, not directly on the raw information of the dictionary. We also set the contribution of dictionaries from this perspective, as a warehouse with the potential to produce lexical-semantic relations between word senses. We think that ontologies and dictionaries have to be joined. Word senses and concepts have to be joined, relations have to be set between sense/concepts, not between words. Chapter IX is devoted to this subject, performing word sense disambiguation on a Dictionary Knowledge Base and linking it to an external ontology.

The best results on applications using relatedness have been achieved using corpus-based measures of relatedness. Corpus-based statistical techniques are becoming very popular in the field of Natural Language Processing, and although they are mostly empiric works, a theoretical frame is also being built-up around the use of corpus. Anyway, when modeling relatedness of concepts, they have had to face several important problems. The first one is the fact that there is **not a direct definition of sense**, there is no link from words to concepts. Some works, therefore, just define relatedness between words (Grefenstette, 1992; 1996; Grishman & Sterling, 1994; Lee, 1997; Golding & Schaves, 1996). This is disturbing from a theoretical point of view, but it also brings further problems in the practical side. In order to be able to extend relatedness to word senses it demands **manual semantic tagging** of corpora (Church & Hanks, 1990; Hearst, 1991)[25]. The main trouble of manual tagging is the amount of handwork needed, as it is a time consuming task. It also rises the question of the accuracy of hand tagging, as sense boundaries are usually quite obscure, and inter-tagger agreement is usually quite low (%32 according to Jorgensen (1990)).

The improvements to the initial corpus-based proposals have been along these lines: how to avoid hand-disambiguation and how to define word sense on some more solid grounds. Schütze (1992a; 1992b) clusters automatically the contexts for a given word. A word will have as many-senses as clusters were derived. Hearst and Schütze (1993) group WordNet classes and link the occurrences of words in corpora to these classes. Accordingly, a word will have as many senses as classes to which it was linked. Yarowsky (1992) also defines word senses according to classes, but in this case with the semantic labels from Roget's thesaurus. Yarowsky himself, in later works (1994; 1995) takes another approach and presents a bootstrapping algorithm that diminishes substantially human tagging. All these works follow an interesting direction, but they never get to give a solid basis to word senses, and they fall short of linking word occurrences to ontology concepts. An attempt is presented in (Leacock et al., 1998), where WordNet is both used as dictionary, and also to diminish hand-tagging, but the results are not encouraging. Although corpus-based techniques have tried hard for many years, there are nowadays very few hand-tagged corpora, and it does not seem that corpus-based techniques will be able to go further than tagging the occurrences of a handful of words.

Corpus-based techniques also have to face the **sparse data problem**. It comes from the fact that words are taken to be isolated tokens, without considering relevant classes or sets. This, although

[25] Gale´s group (Gale et al. 1992; 1993; Yarowsky, 1993) defines senses in a different context, using the translations in parallel texts as word senses. A word will have as many senses as different translations in the parallel text. For a limited application –regarding translation– they eliminate the problem of hand-disambiguation. However, this can not be generalized to other sense or concept definitions, and the theoretical problem of defining what word senses are remains unsolved.

paradoxical in appearance, brings another problem, which can be stated as the **too-much-data problem**. On one hand, in order to alleviate the sparse data problem it is convenient to use the widest corpora possible and collect as many word occurrences as possible. On the other, all word occurrences have to be stored in order to study relatedness properly. Therefore, the information stored for each word in the lexicon is really extensive, and the information obtained for all words is huge. That is for sure, one of the reasons for evaluating corpus-based systems on small word sets[26]. Resnik (1993a; 1993b; 1995; 1997) addresses these problems using WordNet to structure word senses and words into classes. Resnik collects from corpora frequency information for the classes in WordNet, and instead of modeling word-to-word relations directly, he uses the classes (concepts) of the ontology.

As we have also said about dictionaries, we see the corpus as a huge information warehouse, but the information contained should be extracted into a structured representation. The fact that ham and fork are related can be easily derived from corpora, perhaps better than anywhere else. But saying that their relatedness weight is 0,87 should not be enough, the kind of relation should also be stated. In addition, this information should not be kept isolated, obscured in a list of co-occurrences. If the strength of the association, alongside the kind of relation was conveniently compiled, the most significant information could be incorporated into ontologies, in a more explicit and compact manner, and allowing the integration of several inference capabilities. One example of this is the above-mentioned work of Resnik, which represents the selectional restriction of verbs according to the classes of WordNet, compiling word-to-word information into classes.

Measures based on ontology, therefore, hold the strongest theoretical standpoint. Besides, word sense is clearly defined, by means of ontology concepts. The problem of ontologies, however, is one of content. Although the design of ontologies include rich relations and features, it is not easy to give values to relations and features of all concepts in the ontology. The amount of concepts should also cover a sufficient part of the lexicon. When going trough existing ontologies (cf. chapter V) we have mentioned that all ontologies have either a limited coverage of words, or just a few relations included, or both. One of the ontologies with broader lexicon is WordNet, but it mainly includes just hypernymy and synonymy relations. The problem of ontology-based relatedness measures is one of quantity of information: they can use whatever is available in their respective ontology, and no more (see proposals for further work in section X.C.1).

[26] Yarowsky (1992) for example, evaluates on the occurrences of 8 words.

VI.D.2. Conceptual Density and the other ontology-based techniques

Although the works of Tversky and Quillian are interesting, they have been placed aside when building an efficient implementation of relatedness. *Spreading activation* needs to visit all nodes and relations of the semantic network, not once, but several times.

Radar´s group, taking into account the organization of semantic networks, leaves aside all the other relations and began to use only paradigmatic relations, improving efficiency notably. Sussna was the first one to implement Conceptual Distance on WordNet, using paths between two concepts. Not only did he use paradigmatic relations, but also meronimic relations, obtaining a slight improvement in his experiments. Although the implementation has no efficiency problems when computing the distance between two concepts (it has to explore the average depth of the hierarchy twice, which can be achieved using an algorithm with constant order, O(ct)), in order to compute the distance among N words having M average senses pairwise distance has to be computed $\frac{N \times (N-1)}{2} \times M^2$ times (cf. section VI.B.2). This demands an algorithm with $O(N^2)$ complexity. Having in mind that some authors use windows with 100 words, for instance in word sense disambiguation, this problem becomes crucial.

Conceptual Density, on the other hand, computes the density for all the words under consideration at once, processing the $N \times M$ senses only once, and therefore, allowing for an algorithm with lower complexity.

As already mentioned in section VI.B.2, the problem of using pairwise relatedness is not only one of efficiency. In theoretical grounds, it is not very clear what does it mean to add pairwise distances for N concepts, which makes altogether difficult to compare distances among sets with different number of concepts. Conceptual Density, on the contrary, gives us a measure allowing to compare naturally the relatedness of concept sets with differing cardinality.

So as to finish with the examination of Conceptual Density (the evaluation related to the practical results will be given in chapters VII (Agirre & Rigau, 1996a), VIII (Agirre et al., 1998c) and IX (Rigau et al., 1997)), we will reconsider the conditions set beforehand on the goal relatedness measure:

1. It is based on ontologies.
2. Measures relatedness among senses, making reference to ontology concepts.
3. Uses information from paradigmatic and syntagmatic relations.

4. Works for all open-class words.
5. Efficient, so as to be able to work with long texts.
6. The measure works for any number of concepts
7. The measures for sets with different number of concepts are comparable with each other.

From these required features we already saw that Conceptual Density meets 1, 2, 5, 6 and 7. Regarding the 4th condition, we have only tried the Conceptual Density with nouns (cf. chapters VII, VIII and IX), but a priori there is no problem to extend it to the other parts of speech.

Regarding the 3rd requirement, it was already mentioned in chapter V that there is nowadays no freely accessible wide-coverage ontology except WordNet. Conceptual Density, therefore, has been designed having WordNet in mind, and it does only use hypernym and meronym relations. In other words, it does not use any syntagmatic relation.

VII. Chapter

WORD SENSE DISAMBIGUATION

In this chapter we evaluate Conceptual Density in a practical application, and, along the way, adjust the parameters of Conceptual Density mentioned in the previous chapter, considering the results of this application. Even if the previous chapter reasons the theoretical and practical advantages of Conceptual Density, we wanted to show that it also attains good results in practice. In Word sense Disambiguation we have to decide which of the senses for a word was intended for a given test occurrence. Almost all measures of relatedness have been applied to Word sense Disambiguation (mostly in noun disambiguation), and, furthermore, they have been sometimes designed specifically for this purpose. This chapter will start with a study of antecedents, underlining the need of different knowledge sources. Afterwards, we will explain the design of the experiments and the algorithm used to disambiguate with Conceptual Density. The experiment was set on an already disambiguated corpus, so as to automatically measure the precision of the system. From this corpus, we chose four text-sets, and we disambiguated all nouns in the sample (around 2.000 nouns), choosing the word senses from WordNet. A specific section is devoted to study the effects of the parameters and variants of Conceptual Density, and to choose the best values for the parameters. After evaluating the results, we will compare them to those of other methods. We have implemented two other ontology-based methods, obtaining worse results. Finally, the contributions of this chapter are outlined.

This chapter is not available in the English version, but it is fully covered in the papers (Agirre & Rigau, 1995; 1996a; 1996b), that can be found in appendix **A**. The first paper (Agirre & Rigau, 1995; **A.1**) presents some preliminary experiments, which were completed afterwards with the experiments presented in the second paper (Agirre & Rigau, 1996a; **A.2**). Finally, a slightly more extended version was published as an internal report (Agirre & Rigau, 1996b; **A.3**).

VIII. Chapter
AUTOMATIC SPELLING CORRECTION

In this chapter we have developed another practical application, that of automatically correcting spelling errors. In this chapter we introduce the implementation and the design of the system that tries to choose the correct proposal among the set of correction proposals. Firstly we present the literature on this subject. Afterwards, we introduce the results of the feasibility study on semantic and syntax-based correction. We concluded that it was absolutely necessary to include semantic knowledge, and put forward a proposal for the use of relatedness measures on the LKB built from *Le Plus Petit Larousse*. In the following section, the method for automatic correction is proposed, which is based on syntactic knowledge, semantic knowledge (provided by Conceptual Density for nouns) and corpus-based statistical techniques. Next, the design of the experiments is presented alongside the evaluation and comparison with others. Two kinds of corpora were used: one where we introduced spelling errors artificially, and another with real spelling errors. Finally, the contributions of this chapter are summarized.

Regarding the English version, this chapter is fully available in the papers (Agirre, 93; Agirre et al., 1994b; Agirre et al., 1995; Agirre et al., 1998b; Agirre et al., 1998c) that can be found in appendix **B**. The preliminary ideas were presented in Spanish in (Agirre, 1993)[27], specifically the feasibility-study and the preliminary proposal for using the knowledge in the French LKB. A reduced version was published in (Agirre et al., 1995; **B.1**). The proposal for using the relations in the LKB was further elaborated in (Agirre et al., 1994b; **B.2**). The design of the correction system and the actual

[27] This paper is not available.

experiments are described in (Agirre et al., 1998b; 1998c; **B.3** and **B.4**), being the latter the final version.

IX. Chapter
ENRICHING THE DICTIONARY KNOWLEDGE-BASE

This chapter tackles the other main objective of this dissertation, namely, the building of LKB for non-English languages. First of all, lexical knowledge acquisition literature is reviewed, including multilingual resource linking, and the extraction of hierarchies from dictionaries. Hierarchies are usually extracted from dictionaries by analyzing the definitions of the word senses and detecting the hypernymy relation between the entry being defined and a distinguished term in the definition called the *genus*. Special attention is paid to the problems presented by the hierarchies extracted from dictionaries. On the one hand, hierarchies are not usually sense disambiguated. On the other hand, hierarchies tend to be shallow and isolated from each other, to exhibit coherency problems in the top layer. Part of the problems of shallowness and isolation is caused by the cycles in the extracted hierarchies and the fact that some word senses are left out of the hierarchies (generally those defined using specific relators, which do not contain a genus). Our position and proposal to overcome these problems is presented next.

In order to check whether it is possible to strengthen the construction of LKBs or not, we have studied the DKB extracted form *Le Plus Petit Larousse*. As to make this DKB a LKB usable in NLP, we have to solve the shortcomings explained above. We propose an integrated solution method. Firstly, we studied the definitions producing cycles in the hierarchy and the relator type of definitions, and we linked all these entries to an external LKB, WordNet (in fact, we linked all entries in LPPL). These links will enable us to integrate the mentioned problematic definitions in the overall hierarchies. Secondly, we automatically disambiguated the hierarchies, producing a word sense hierarchy. Finally, we have used the LPPL-WordNet links to connect all the isolated hierarchies (including those produced by breaking the cycles and by specific relator definitions) taking WordNet as a reference. In other words, we connected the isolated hierarchies using the WordNet hierarchy. By the way, the top layer of WordNet is incorporated in the extracted hierarchy, solving the lack of coherence that hierarchies extracted from dictionaries exhibit.

In order to link the word senses of the DKB extracted from LPPL to WordNet, we used a bilingual dictionary and Conceptual Density, so that we can assign one WordNet concept (or more) to each sense of LPPL. So as to disambiguate the hierarchy, we will use both the knowledge in the dictionary itself and the link to WordNet. We have implemented several independent techniques for disambiguation, including Conceptual Density, which were combined using a voting strategy.

This chapter is not fully covered in English. The work on cycles and the treatment of specific relators is yet unpublished in English. The two papers related to this chapter cover the method to link LPPL to WordNet (Rigau & Agirre, 1995; **C.1**) and the method to disambiguate the hierarchies extracted from LPPL (Rigau et al., 1997; **C.2**). Both papers are included in appendix **C**. The latter has been further improved as explained in (Rigau et al., 1998) but these improvements have not been covered in the present dissertation. The results for the connection of the isolated hierarchies are unavailable in English.

X. Chapter
CONCLUSIONS

X.A. Summary

The main contributions of this work are two:

a. A formalization of relatedness: Conceptual Density

b. A method to enrich and strengthen hierarchies extracted from dictionaries

We formalized a measure for the relatedness between word senses: Conceptual Density. This measure is based on ontologies, and therefore, re-utilizes information used for general NLP. It can be applied to any ontology, it does not need any previous preparation, and it is able to operate in all the fields covered by the ontology. We implemented Conceptual Density for nouns on WordNet.

We claim that our formalization is more interesting than both measures based on other lexical resources (corpora or dictionaries) and other measures based on ontologies. We reasoned this position in chapter III, but we also tried to show its advantages in practice:

- In Word sense Disambiguation (chapter IV)
- In Automatic Spelling Correction (chapter V)

Conceptual Density performs well in word sense disambiguation of nouns, although the comparison with other systems is difficult. In order to compare them better, we implemented two other ontology-based systems, which did not perform as well as Conceptual Density on the same test-set. The results in automatic spelling correction were not so conclusive. As the current implementation of Conceptual Density only works for nouns, we could only apply it when all the correction proposals were nouns, and therefore, it was seldom used in the test corpora. The automatic spelling correction system introduced in this dissertation uses additional knowledge sources.

Concerning the second main contribution, we presented a method to enrich and strengthen the hierarchies extracted from dictionaries. This method uses both Conceptual Density on WordNet and the knowledge contained in the dictionary under study. We have improved the hierarchies extracted from the *Le Plus Petit Larousse* French dictionary in two main areas:

- Linking the entries and genus from the French dictionary *Le Plus Petit Larousse* to WordNet synsets using a bilingual dictionary.
- Sense-disambiguating and strengthening the hierarchies of the DKB extracted from *Le Plus Petit Larousse*.

Thanks to the first one, we can overcome some shortcomings of the extracted hierarchies, using the hierarchy of WordNet as a top ontology to do the following: join the definitions with specific-relators, erase the cycles in the hierarchy, join isolated mini-hierarchies and give all hierarchies a coherent top level. It also supports the disambiguation of word-based hierarchies into word sense based hierarchies. The method can be applied to disambiguate and strengthen hierarchies taken from any dictionary.

Besides, the method can be also used to join lexical resources, and it could be also used to link heterogeneous resources, in the same language or in different ones: ontologies to LKBs, LKBs to LKBs and so on. This opens new perspectives for the enriching of lexical resources, as languages poor in linguistic knowledge can absorb the knowledge built for English, provided this knowledge can be readily applied to the other language, of course. Word sense disambiguation, from this perspective, can also be cast as a method to join lexical resources, that is, to link the occurrences of the words in the corpus to word senses/concepts in the ontology. This point of view offers new paths to enrich ontologies.

Regarding future-work, we see a great demand of both wide-coverage and relation-rich ontologies. In fact, Conceptual Density as implemented in this dissertation, only takes advantage of the information in WordNet, that is, of mostly paradigmatic relations. Although we obtained good results in the tasks where Conceptual Density was applied, it is also clear that syntagmatic relations offer good perspectives of improvement, for example in word sense disambiguation, but specially in automatic spelling-correction, in order to extend the contribution of Conceptual Density.

We think that a close coordination between corpora, dictionaries and ontologies is needed to perform word sense disambiguation, but also to offer a robust solution for other lexical-semantic problems in NLP. Chapter VI (Rigau & Agirre, 1995) shows a method to join a LKB (WordNet) and a DKB (*Le Plus Petit Larousse*) in different languages. This integration can be used to enrich WordNet with the information in other LKBs or DKBs, but it would not be sufficient to gather all the needed knowledge for WSD. For instance, regarding syntagmatic relations, there are no wide-coverage lists of selectional restrictions. In oder to be able to favour their learning, we have to support the analysis and use of the definitions in the dictionaries (for example, using the techniques mentioned in chapter VI), which can be integrated in the ontologies once the words in the definitions are disambiguated. Corpora are also a valuable source of information. In chapter III we present several statistical measures based on corpora that capture quite well relatedness for words, and argues that the underlying relations should be coded in ontologies. By means of word sense disambiguation it would be possible to convert these relations between words in relations between word senses taken from a given reference ontology and, therefore, the relations could be added to the ontology. Extending Conceptual Density in an appropriate way, we would take advantage of the relations of these new ontologies, coded in a robust and efficient representation, so as to calculate relatedness using knowledge which was gathered from many different sources.

First, let's study, in more depth, the main contributions made in each chapter. Then, we will present the future-work related to each subject of this dissertation.

X.B. Contributions

X.B.1. A measure of relatedness: Conceptual Density (chapter III)

We have designed and implemented Conceptual Density, which formalizes relatedness among word senses based on ontologies. Conceptual Density takes advantage of paradigmatic relations – hypernimy and meronimy– , and works with nouns at present, although it can also be adequate for verbs.

It shares many features with other formalizations based on ontologies. Being ontologies the main model for knowledge representation in psycholinguistics and artificial intelligence[28], they have a strong theoretical basis. They offer a measure between word senses, with a solid foundation for sense differentiation, given by the senses being linked to ontology concepts. Besides, they do not require any kind of hand disambiguation, and do not show sparse-data or too-much-data problems. These are positive features as compared with other corpora or dictionary-based techniques.

[28] We want to underline that we adopt general definition of ontology, which includes all symbolic knowledge bases.

Measures based on ontologies, however, do have efficiency problems. Furthermore, the measure of relatedness is limited to two concepts, and no more. Conceptual Density overcomes these two limits. It can measure the relatedness for any number of concepts, offering the possibility of comparing the relatedness of sets with different numbers of concepts. It is efficient enough to work with large noun sets from real texts.

X.B.2. Application of CD: Word Sense Disambiguation (chapter IV)

We implemented and tested a disambiguator based on Conceptual Density, which uses the paradigmatic knowledge in WordNet. Thanks to the features of Conceptual Density, we developed a system that disambiguates according to the word senses in the ontology, and is capable of disambiguating the nouns in real running texts. It can be applied to any kind of text, without any adaptation.

As for the results of the experiment, we have proved that Conceptual Density is useful for WSD, and we have seen that it attains better results than two other formalizations of relatedness based on paradigmatic knowledge in WordNet –Sussna (1993) and Yarowsky (1992)–.

When comparing it with other experiments in the WSD literature, ours tackles the most difficult aspects of the problem: fine-grained sense distinction, real texts from different genres, all nouns in the text, leaving aside partial results and accepting one single sense. The texts chosen at random (10.000 words overall) were not at all easy to disambiguate. However, when disambiguating sense distinctions on the fine-grained level in WordNet, we obtained a precision of 64%, and one of 71% if we disambiguated to a coarser file level. Coverage is very wide, as we disambiguated 86% of the nouns in the text.

X.B.3. Application of CD: Automatic Spelling Correction (chapter V)

We designed and implemented a system that performs the automatic correction of running texts, choosing the correct proposal for non-word spelling errors. On the one hand, we proved that automatic spelling-correction is close to be a feasible task with current technologies, and, on the other, we saw that the contribution of Conceptual Density was modest.

This system combines different kinds of knowledge: syntactic (Constraint Grammar), lexical-semantic (Conceptual Density), frequency of words, context-based statistical measures and specific heuristics. Thanks to Constraint Grammar, frequency of words in documents and context-based statistics, the system is able to choose a single proposal for 24 out of 25 errors (two proposals for the rest) with 90% precision, and 100% coverage. These results prove that automatic spelling-correction can be performed nowadays with current technology.

Conceptual Density could be applied to 8% of all errors, as it is only applied whenever all proposals are nouns. Although the sample is too small to provide reliable data, it attained 75% precision. The reason for this modest performance is not CD itself, but the shortcomings of the knowledge in WordNet, as pointed down in chapter III.

X.B.4. Techniques to enrich and strengthen structured lexical resources (chapter VI)

The problems exhibited by hierarchies extracted from dictionaries are mentioned at the beginning of chapter VI, and the hierarchies extracted from *Le Plus Petit Larousse* (Artola, 1993) are not an exception. So as to solve these problems we saw the need of an external ontology, which would organize the top-levels of the hierarchies and would link the different hierarchies in a single structure. Besides, we also used the links to the external ontology in order to solve cycles in the hierarchy, and to integrate the definitions with specific-relators in the hierarchies. This external ontology has also been the key to disambiguate the words in hierarchies. We organized the overall method to strengthen and enrich hierarchies extracted from dictionaries in four parts:

X.B.4.a) Treatment of cycles and definitions with specific-relators

We introduced a method to break the cycles and to integrate them in the hierarchies, which uses the LPPL-WordNet link. Thanks to the method presented we were able to break all the cycles in the LPPL-derived hierarchies. The method to integrate the otherwise isolated definitions with specific-relators was able to link 78% of such definitions to a sense-disambiguated hypernym in the hierarchy, and 63% to a WordNet synset. The attained precision of both types of links is around 90%. As a result, all the cycles are normally integrated in hierarchies, and almost all the specific-relator definitions are either integrated in the hierarchy or linked to WordNet. Afterwards, the method for linking isolated hierarchies, will also integrate those specific-relator definitions which were only linked to WordNet.

X.B.4.b) Linking resources in different languages at a concept-level

First of all, we automatically linked the senses of a French-English bilingual dictionary to concepts of WordNet (bilingual-WordNet link), using just Conceptual Density. By means of this method, we linked 43% of the noun senses with a precision of 95%. This type of links is very important to link words from foreign languages to a given ontology. In fact, simpler methods have been used with the same goal, e.g. to join Spanish words to the Sensus ontology (Okumura & Hovy, 1994), and also, within the EuroWordNet project, to build the Spanish WordNet (Rigau & Agirre, 1995;

Atserias et al. 1997). We think that the method presented here using Conceptual Density would help to improve the precision reached in those works.

Regarding the method to join the entries and genus of LPPL to WordNet concepts (LPPL-WordNet link), the bilingual-Wordnet links have been valuable to improve the results. Apart from these links, we made use of Conceptual Density, hypernimy relations, some simple heuristics and saliency-based statistical information, including also the treatment of the specific-relator kind of definitions. Altogether, we have been able to link 87% of the noun senses of the entries in LPPL to WordNet synsets, with a precision of 80%. Both Conceptual Density and the heuristic using hypernimy relations are based on the paradigmatic links of WordNet. The technique using saliency employs statistical measures on the words in the definitions and the semantic codes in WordNet.

X.B.4.c) Genus disambiguation

In this work, we have shown that genus disambiguation is not only limited to special English dictionaries such as LDOCE, since we developped a method that attains a precision of 82% on the hierarchies of LPPL. This method can be applied to any other dictionary, as the results obtained with a Spanish dictionary – 83% precision– show (Rigau et al. 1997).

X.B.4.d) Linking isolated hierarchies extracted from dictionaries

Hierarchies derived from dictionary definitions, even after disambiguation, exhibit several deficiencies: most of them are small and isolated from each other, without any link between them. Besides, it is also known that the top layer of such hierarchies is not very adequate. We have proposed a method that tries to solve both problems, taking advantage of the links to WordNet that were already computed. In this procedure we link the root of the isolated hierarchies to WordNet, using the upper layer of WordNet to provide a coherent upper level to our hierarchy as well, and by the way linking all isolated hierarchies to each other via WordNet relations. The proposed method is general, and it will be also possible to join the hierarchies extracted from dictionaries to any ontology, giving us the opportunity of choosing the most interesting top level.

X.C. Future Work

X.C.1. Improvement of Conceptual Density (chapter III)

We see three main avenues to improve Conceptual Density:

- Regarding the information used: To either obtain a richer ontology providing syntagmatic relations and selectional restrictions, or to enrich WordNet with those relations from elsewhere. Unfortunately, this information is not readily available at present, but methods to extract them automatically from dictionaries and corpora are being studied. We have already mentioned in section X.B.4, for instance, that it is possible to extract syntagmatic relations from the analysis of the differentia in dictionary definitions. In the chapter on automatic spelling correction (chapter V), we have also seen that the raw information gathered by context statistics from corpora hides implicit syntagmatic relations and selectional-restrictions. Thanks to the integration of lexical resources (chapter VI) and word sense disambiguation (chapter IV), it would be possible to integrate this information in the knowledge-base of WordNet.

- Regarding the formula: To change the Conceptual Density formula, so that it includes syntagmatic relations. In section V.B.2, we have shortly described how syntagmatic relations can be integrated in Conceptual Density, along the lines proposed in (Agirre et al. 1994b) for an efficient conceptual distance concerning both paradigmatic and syntagmatic relations from LPPL.

- Faster implementation: Even if the complexity of the Conceptual Density algorithm is acceptable, we think that a faster implementation can be obtained. One of the reasons for that is that LISP has been the implementation language, and the other one, that the access to the information in WordNet is not optimized. The research group of the Electricity and Electronic Department of the UNED is developing a version on C++, within the ITEM[29] project. This version will be soon integrated in the GATE[30] environment for linguistic engineering (Cunningham et al. 1997), in the module for word sense-disambiguation.

X.C.2. Word Sense Disambiguation (Chapter IV)

The design of the experiments could be improved as follows:

- Disambiguating text chunks in one go, following discourse-structure. This way, instead of disambiguating words one by one using a context window, whole parts of the text, e.g. paragraphs, can be disambiguated altogether, improving efficiency. Besides, precision would also improve, as unrelated text parts would be treated separately.

- It would be interesting to study whether there is any correlation between the measure of density and the correct choice of sense. If that was the case, we would leave the cases with density below a certain measure ambiguous, and precision would improve (at the cost of a lower coverage).

[29] http://sensei.ieec.uned.es/item/

If we want to build a more powerful system for WSD, in addition to the improvements to Conceptual Density outlined in the previous section, it is necessary to supplement relatedness measures with other useful information sources: For instance, frequencies of word sense, both overall and local to the text we are disambiguating, whether the sense appears always as a collocation, information about the syntactic structure around the word sense, and so on. We would thus build a more thorough system for sense-disambiguation, which would code lexical-semantic information by means of Conceptual Density, and which would be able to combine this with other knowledge.

While this dissertation is being written, we are also preparing the SENSEVAL competition[31]. Many groups world-wide are going to present their systems. For this competition, we will try to combine Conceptual Density with several dictionary techniques (related to those used in chapter VI) and present a disambiguation system that does not need any training. We also plan to present an additional system, which will combine the previous with a context-based trainable system (cf. chapter V).

X.C.3. Automatic Spelling Correction (Chapter V)

When designing the experiment we did not bear in mind that the learning corpus (Brown) and the testing corpus (Bank of English) were from different dialects. It is for sure that this mismatch affects negatively to the results of the overall frequency and techniques based on context-statistics. The best solution would be to learn from the held-out data of the Bank of English, but, unfortunately, there are serious limitations to get the data. Consequently, the corpus of real-errors had a very small context window around the error (more or less one sentence). This has seriously damaged the heuristic that proved to be most powerful, i.e. the document frequency, which needs to gather frequencies from whole documents, not just the sentence around the error. We are trying to overcome these limitations, which would improve strongly our results.

In order to improve precision we should refine the knowledge used. Constraint Grammar, for example, can be better adapted to deal texts with misspellings, since the version we used was not designed for that. Conceptual Density, would also get better results, specially in coverage, if WordNet was enriched with syntagmatic relations, allowing to tackle proposals from different categories.

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30 http://www.dcs.shef.ac.uk/research/groups/nlp/gate/

31 http://www.itri.bton.ac.uk/events/senseval/cfp2.html

Finally, the results in this task do not ratify (nor deny) one of the features of Conceptual Density that we mentioned in chapter III, i.e. the fact that it can also be used to measure relatedness between words. In the algorithm for automatic spelling correction we have chosen the proposal that had the word sense with the highest density, but we should also try other possibilities like, for instance, adding the densities for all word senses of each proposal, and choosing the proposal with the highest overall density.

X.C.4. Strengthen and enrich lexical resources further (Chapter VI.)

X.C.4.a) Multilingual links between concepts

Using wider bilingual dictionaries would improve the coverage and precision in the LPPL-WordNet link. On the one hand, we would have a wider Bilingual-WordNet link (enabling for more coverage and precision in the LPPL-WordNet link). On the other, the lack of translation for a word sense in LPPL is a serious error-source, and a wider bilingual dictionary would reduce those (better precision).

Another opportunity to raise the coverage of the Bilingual-WordNet link is given by the heuristics based on French-word/English-word couples as used in (Okumura & Hovy, 1994; Rigau & Agirre, 1995; Atserias et al. 1997). These heuristics are being successfully used to build the Spanish and Basque WordNets included in the EuroWordNet project. Nevertheless, these word couples have also their drawbacks, since bilingual senses are not taken into account.

Thanks to the use of bilingual senses, WordNet and LPPL could be enriched with the supplementary information appearing in bilingual dictionaries, e.g. collocational information (Fontenelle, 1997).

At present, we are building the Basque WordNet, linked to the EuroWordNet and ITEM projects, making use of the techniques presented in chapter VI and the word couples that we have just mentioned applied to a Basque-English bilingual dictionary (Aulestia & White, 1982). The Spanish WordNet currently under construction, could be also fed into the Basque WordNet using a Basque-Spanish dictionary (Elhuyar, 1996). Using several bilingual dictionaries (Basque-Spanish, Basque-English and Spanish-English) coverage and precision could be improved.

The methods developed for this chapter can be used to join structured lexical resources in general, and this can have a heavy impact on the construction of future ontologies and LKBs. A given resource can be fed with the knowledge in another (in the same language or in a different one), and this looks like a promising avenue in the building of richer ontologies, following the proposals of the *ANSI Ad Hoc* committee on *Ontology Standards*[32] (Hovy, 1997a; 1997b).

X.C.4.b) Genus disambiguation

Although the obtained results are very good, there is still room for improvement. As proposed in a joint paper (Rigau et al. 1998), after applying the Genus disambiguation techniques (cf. chapter VI) on the DGILE (Alvar, 1987) Spanish dictionary, we clustered the genus according to the WordNet semantic code assigned. If only the senses appearing more frequently for each semantic code are considered, precision improves considerably, at the cost of coverage. We tried this method on LPPL too, but due to the small size of the dictionary, the frequencies were not high enough, and precision did not improve.

The research made in conjunction with the computational lexicography group in the Polytechnic University of Catalonia suggests that the developed method is successful with both small and large dictionaries. From larger dictionaries we get wider and more interesting hierarchies, offering also better choices for improvement.

Regarding the voting results, we think it would be interesting to analyze more sophisticated methods. In a small study, we observed that considering only decisions involving a majority of at least 5 heuristics, precision would rise up to 95%, but reducing coverage down to 18%.

On the other hand, when disambiguating, we just used the information in the definition itself. We also plan to disambiguate whole hierarchies. For instance, when disambiguating a given genus, we could bear in mind the hyponyms and hypernyms of each sense of the genus and the disambiguated hyponyms of the definiendum.

In the same way, after linking the disambiguated hierarchies to the top layer of WordNet, we can take advantage of the extra information and try to re-disambiguate the hierarchies.

X.C.4.c) Linking isolated hierarchies extracted from dictionaries

When building the hierarchies, we have not taken into account the synonymy relation. Most of the literature does not pay any attention to synonymy as extracted from dictionaries, but in the case of LPPL many definitions of nouns give just synonyms (the 20% of all word senses). Artola (1993), in the LKB extracted from LPPL, copied the extracted relations between synonyms, and it would be interesting to evaluate the impact of such a method in the disambiguated hierarchy. Other

[32] http://ksl-web.stanford.edu/onto-std/

approaches for the representation of synonymy, such as grouping all synonym word senses in a single concept (WordNet), would have to be studied too.

Although the method to link isolated hierarchies using the top layer of WordNet gave promising results, the quality of the obtained hierarchy was not thoroughly evaluated. At present, there is no agreed procedure to evaluate the quality of ontologies, apart from the number of correct hyponym/hypernim links, which we already provided (82%). This measure being very limited, it could be interesting to evaluate the method according to the usefulness for a given task, like information retrieval, for instance. Besides, we can not forget the *ANSI ad hoc Ontology Standards Group*, already mentioned, which is working also on ontology evaluation guidelines, without any published result for the time being.

X.C.4.d) *Vicious circle*

Among the three main tasks, that is, the LPPL-WordNet link, the disambiguation of genus in LPPL and the building of the top layer to connect the isolated hierarchies of LPPL, we have complex interrelations. In this dissertation, we have performed them sequentially, in the order just mentioned, but the interrelations among the three procedures would have to be better studied. Once the hierarchies of LPPL have been disambiguated and joined by means of the top layer of WordNet (via LPPL-WordNet links), we have more information to do the LPPL-WordNet link, as we are now linking full hierarchies, an21d better results can be expected. Besides, as mentioned above, after building the top layer, genus disambiguation would be easier. Moreover, with better bilingual links, both genus disambiguation and the top layer would improve. An iterative process suggests itself.

Another interesting approach could be the use of neural nets. All the results described in chapter VI –LPPL-WordNet link, the disambiguated hyponym/hypernim relations from LPPL, WordNet hierarchy– can be represented as an arch in a neural net. If we design an appropriate energy function, we can apply known techniques so as to find the optimal combination of arcs. Such a neural net would decide at the same time the best WordNet link and hypernym for a given LPPL sense.

X.C.4.e) *Others*

Even if we have studied the automatic construction and enrichment of LKBs, we have not explored all its implications. For instance, the **extraction from the *differentia*** in the definitions (Artola, 1993) was not touched. The use of the differentia has always been considered interesting and current work (see, for example, Richardson, 1997) shows a renewal of interest in this area.

Besides, we also think that the analysis of the example sentences can give complementary information, as they give interesting information about the context of the word sense.

The automatic building of multilingual hierarchies is a field close to this dissertation. When linking structured resources of different languages, we are implicitly building multilingual hierarchies. In fact, this involves studying whether it is possible to feed the information of ontologies in a given language (semi) automatically into another language. At the same time, questions arise such as whether we can build universal hierarchies, whether information from different hierarchies are compatible, whether it is convenient to link automatically the top layers, etc.

Regarding Basque, we have to mention the work carried out by our research group on the **Euskal Hiztegia** (Sarasola, 1997). The goal of this project is to extract a wide LKB for Basque, rich in semantic information. We have performed the study of the structure of the dictionary and translated following the TEI guidelines (Arriola et al. 1995; 1996a; 1996b). We have concluded the search of genus and special relators for noun definitions (Agirre et al. 1998), and are currently carrying out the analysis for verbs and adjectives, the analysis of example sentences, and the link to WordNet. Next, we plan to construct the disambiguated hierarchies for noun, verb and adjectives, following the method presented in chapter VI. Moreover, the study of the sublanguage used in the definitions of the Basque Dictionary is going on, and we will soon apply superficial syntactic techniques to extract further relations from the *differentia*.

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Appendix A.

Code	Erref	Title	Chapters
A.1	Agirre & Rigau, 1995	A proposal for Word Sense Disambiguation using Conceptual Distance	III and IV
A.2	Agirre & Rigau, 1996a	Word Sense Disambiguation using Conceptual Density	III and IV
A.3	Agirre & Rigau, 1996b	An Experiment on Word Sense Disambiguation of the Brown corpus using WordNet	III and IV

Agirre, E. and Rigau, G. 1995. A proposal for Word Sense Disambiguation using Conceptual Distance, in *Proc. of the Conference on Recent Advances in Natural Language Processing* (Tzigov Chark, Bulgary).

Agirre, E. and Rigau, G. 1996a. Word Sense Disambiguation using Conceptual Density, in *Proc. of COLING* (Copenhagen, Denmark).

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Appendix B.

Code	Erref	Title	Chapters
B.1	Agirre et al., 1994b	Conceptual Distance and Automatic Spelling Correction	III and V
B.2	Agirre et al., 1995	Lexical-Semantic Information and Automatic Correction of Spelling Errors	V
B.3	Agirre et al., 1998b	Towards a Single Proposal in Spelling Correction	V
B.4	Agirre et al., 1998c	Towards a Single Proposal in Spelling Correction	V

Agirre, E., Arregi, X., Artola, X., Díaz de Ilarraza, A., Sarasola, K. 1994b. Conceptual Distance and Automatic Spelling Correction, in *Proc. of the Workshop on Computational Linguistics for Speech and Handwriting Recognition* (Leeds, England).

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Appendix C.

Code	Erref	Title	Chapters
C.1	Rigau & Agirre, 1995	Disambiguating bilingual nominal entries against WordNet	VI
C.2	Rigau et al., 1997	Combining Unsupervised Lexical Knowledge Methods for Word Sense Disambiguation	VI

Rigau, G. and Agirre, E. 1995. Disambiguating bilingual nominal entries against WordNet, in *Workshop On The Computational Lexicon - ESSLLI* (Barcelona, Catalonia).

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A Proposal for Word Sense Disambiguation using Conceptual Distance

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Abstract.

This paper presents a method for the resolution of lexical ambiguity and its automatic evaluation over the Brown Corpus. The method relies on the use of the wide-coverage noun taxonomy of WordNet and the notion of conceptual distance among concepts, captured by a Conceptual Density formula developed for this purpose. This fully automatic method requires no hand coding of lexical entries, hand tagging of text nor any kind of training process. The results of the experiment have been automatically evaluated against SemCor, the sense-tagged version of the Brown Corpus.

Keywords: Word Sense Disambiguation, Conceptual Distance, WordNet, SemCor.

1 Introduction

Word sense disambiguation is a long-standing problem in Computational Linguistics. Much of recent work in lexical ambiguity resolution offers the prospect that a disambiguation system might be able to receive as input unrestricted text and tag each word with the most likely sense with fairly reasonable accuracy and efficiency. The most extended approach is to attempt to use the context of the word to be disambiguated together with information about each of its word senses to solve this problem.

Several interesting experiments have been performed in recent years using preexisting lexical knowledge resources. (Cowie et al. 92) describe a method for lexical disambiguation of text using the definitions in the machine-readable version of the LDOCE dictionary as in the method described in (Lesk 86), but using simulated annealing for efficiency reasons. (Yarowsky 92) combines the use of the Grolier encyclopaedia as a training corpus with the categories of the Roget's International Thesaurus to create a statistical model for the word sense disambiguation problem with excellent results. (Wilks et al. 93) perform several interesting statistical disambiguation experiments using coocurrence data collected from LDOCE. (Sussna 93), (Voorhees 93), (Richarson et al. 94) define a disambiguation programs based in WordNet with the goal of improving precision and coverage during document indexing.

Although each of these techniques looks somewhat promising for disambiguation, either they have been only applied to a small number of words, a few sentences or not in a public domain corpus. For this reason we have tried to disambiguate all the nouns from real texts in the public domain sense tagged version of the Brown corpus (Francis & Kucera 67), (Miller et al. 93), also called Semantic Concordance or Semcor for short. We also use a public domain lexical knowledge source, WordNet (Miller 90). The advantage of this approach is clear, as Semcor provides an appropriate environment for testing our procedures in a fully automatic way.

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This paper presents a general automatic decision procedure for lexical ambiguity resolution based on a formula of the conceptual distance among concepts: Conceptual Density. The system needs to know how words are clustered in semantic classes, and how semantic classes are hierarchically organised. For this purpose, we have used a broad semantic taxonomy for English, WordNet. Given a piece of text from the Brown Corpus, our system tries to resolve the lexical ambiguity of nouns by finding the combination of senses from a set of contiguous nouns that maximises the total Conceptual Density among senses.

Even if this technique is presented as stand-alone, it is our belief, following the ideas of (McRoy 92) that full-fledged lexical ambiguity resolution should combine several information sources. Conceptual Density might be only one evidence of the plausibility of a certain word sense.

Following this introduction, section 2 presents the semantic knowledge sources used by the system. Section 3 is devoted to the definition of Conceptual Density. Section 4 shows the disambiguation algorithm used in the experiment. In section 5, we explain and evaluate the performed experiment. In section 6, we present further work and finally in the last section some conclusions are drawn.

2 WordNet and the Semantic Concordance

Sense is not a well defined concept and often has subtle distinctions in topic, register, dialect, collocation, part of speech, etc. For the purpose of this study, we take as the senses of a word those ones present in WordNet 1.4. WordNet is an on-line lexicon based on psycholinguistic theories (Miller 90). It comprises nouns, verbs, adjectives and adverbs, organised in terms of their meanings around semantic relations, which include among others, synonymy and antonymy, hypernymy and hyponymy, meronymy and holonymy. Lexicalised concepts, represented as sets of synonyms called synsets, are the basic elements of WordNet. The senses of a word are represented by synsets, one for each word sense. The version used in this work, WordNet 1.4, contains 83,800 words, 63,300 synsets (word senses) and 87,600 links between concepts.

The nominal part of WordNet can be viewed as a tangled hierarchy of hypo/hypernymy relations. Nominal relations include also three kinds of meronymic relations, which can be paraphrased as member-of, made-of and component-part-of.

SemCor (Miller et al. 93) is a corpus where a single part of speech tag and a single word sense tag (which corresponds to a WordNet synset) have been included for all open-class words. SemCor is a subset taken from the Brown Corpus (Francis & Kucera, 67) which comprises approximately 250,000 words out of a total of 1 million words. The coverage in WordNet of the senses for open-class words in SemCor reaches 96% according to the authors. The tagging was done manually, and the error rate measured by the authors is around 10% for polysemous words.

3 Conceptual Density and Word Sense Disambiguation

A measure of the relatedness among concepts can be a valuable prediction knowledge source to several decisions in Natural Language Processing. For example, the relatedness of a certain word-sense to the context allows us to select that sense over the others, and actually disambiguate the word. Relatedness can be measured by a fine-grained conceptual distance (Miller & Teibel, 91) among concepts in a hierarchical semantic net such as WordNet. This measure would allow to discover reliably the lexical cohesion of a given set of words in English.

Conceptual distance tries to provide a basis for determining closeness in meaning among words, taking as reference a structured hierarchical net. Conceptual distance between two concepts is defined in (Rada et al. 89) as the length of the shortest path that connects the concepts in a hierarchical semantic net. In a similar approach, (Sussna 93) employs the notion of conceptual distance between network nodes in order to improve precision during document indexing. Following these ideas, (Agirre et al. 94) describes a new conceptual distance formula for the automatic spelling correction problem and (Rigau 94), using this conceptual distance formula, presents a methodology to enrich dictionary senses with semantic tags extracted from WordNet.

The measure of conceptual distance among concepts we are looking for should be sensitive to:

• the length of the shortest path that connects the concepts involved.

• the depth in the hierarchy: concepts in a deeper part of the hierarchy should be ranked closer.

• the density of concepts in the hierarchy: concepts in a dense part of the hierarchy are relatively closer than those in a more sparse region.

• the measure should be independent of the number of concepts we are measuring.

We have experimented with several formulas that follow the four criteria presented above. Currently, we are working with the Conceptual Density formula, which compares areas of subhierarchies.

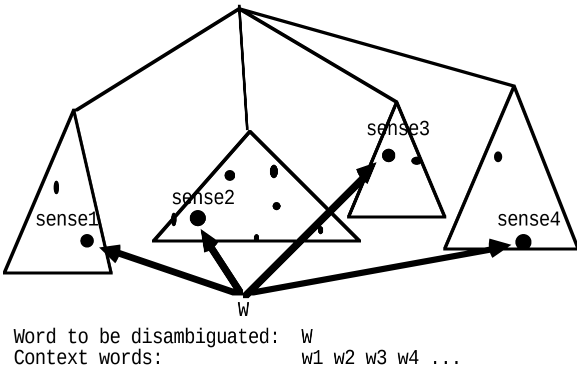

Figure 1: senses of a word in WordNet

As an example of how Conceptual Density can help to disambiguate a word, in figure 1 the word W has four senses and several context words. Each sense of the words belongs to a subhierachy of WordNet. The dots in the subhierarchies represent the senses of either the word to be disambiguated (W) or the words in the context. Conceptual Density will yield the highest density for the subhierarchy containing more senses of those, relative to the total amount of senses in the subhierarchy. The sense of W contained in the subhierarchy with highest Conceptual Density will be chosen as the sense disambiguating W in the given context. In figure 1, sense2 would be chosen.

Given a concept *c*, at the top of a subhierarchy, and given *nhyp* and *h* (mean number of hyponyms per node and height of the subhierarchy, respectively), the Conceptual Density for *c* when its subhierarchy contains a number *m* (marks) of senses of the words to disambiguate is given by the formula below:

$$\mathrm{CD}(c,m) = \frac{\sum_{i=0}^{m-1} \mathrm{nhyp}^i}{\sum_{i=0}^{h-1} \mathrm{nhyp}^i} \qquad \textbf{(1)}$$

The numerator expresses the expected area for a subhierarchy containing *m* marks (senses of the words to be disambiguated), while the divisor is the actual area, that is, the formula gives the ratio between weighted marks below *c* and the number of descendant senses of concept *c*. In this way, formula 1 captures the relation between the weighted marks in the subhierarchy and the total area of the subhierarchy below *c*. The weight given to the marks tries to express that the height and the number of marks should be proportional.

nhyp is computed for each concept in WordNet in such a way as to satisfy equation 2, which expresses the relation among height, averaged number of hyponyms of each sense and total number of senses in a subhierarchy if it were homogeneous and regular:

$$\mathrm{descendants}_c = \sum_{i=0}^{h-1} \mathrm{nhyp}^i \qquad \textbf{(2)}$$

Thus, if we had a concept *c* with a subhierarchy of height 5 and 31 descendants, equation 2 will hold that *nhyp* is 2 for *c*.

Conceptual Density weights the number of senses of the words to be disambiguated in order to make density equal to 1 when the number *m of* senses below *c* is equal to the height of the hierarchy *h*, to make density smaller than 1 if *m* is smaller than *h* and to make density bigger than 1 whenever *m* is bigger than *h*. The density can be kept constant for different *m*-s provided a certain proportion between the number of marks *m* and the height *h* of the subhierarchy is maintained. Both hierarchies **A** and **B** in figure 2, for instance, have Conceptual Density 1.

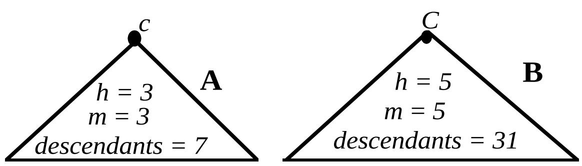

Figure 2: two hierarchies with CD = 1[1].

[1]*From formulas 1 and 2 we have:*

$$descendants(c) = 7 = \sum_{i=0}^{3-1} nhyp^i \Rightarrow nhyp = 2 \Rightarrow CD(c,3) = \sum_{i=0}^{3-1} 2^i \Big/ 7 = 7/7 = 1$$

$$descendants(c) = 31 = \sum_{i=0}^{5-1} nhyp^i \Rightarrow nhyp = 2 \Rightarrow CD(c,5) = \sum_{i=0}^{5-1} 2^i \Big/ 31 = 31/31 = 1$$

In order to tune the Conceptual Density formula, we have made several experiments adding two parameters, α and β. The a parameter modifies the strength of the exponential *i* in the numerator because *h* ranges between 1 and 16 (the maximum number of levels in WordNet) while *m* between 1 and the total number of senses in WordNet. Adding a constant b to *nhyp*, we tried to discover the role of the averaged number of hyponyms per concept. Formula 3 shows the resulting formula.

$$CD(c,m) = \frac{\sum_{i=0}^{m-1} (nhyp+\beta)^{i^{\alpha}}}{descendants_c} \qquad \textbf{(3)}$$

After an extended number of runs which were automatically checked, the results showed that β does not affect the behaviour of the formula, a strong indication that this formula is not sensitive to constant variations in the number of hyponyms. On the contrary, different values of α affect the performance consistently, yielding the best results in those experiments with α near 0.20. The actual formula which was used in the experiments was thus the following:

$$CD(c,m) = \frac{\sum_{i=0}^{m-1} nhyp^{i^{0.20}}}{descendants_c} \qquad \textbf{(4)}$$

4 The Disambiguation Algorithm Using Conceptual Density

Given a window size, the program moves the window one word at a time from the beginning of the document towards its end, disambiguating in each step the word in the middle of the window and considering the other words in the window as context.

The algorithm to disambiguate a given word w in the middle of a window of words W roughly proceeds as follows. First, the algorithm represents in a lattice the nouns present in the window, their senses and hypernyms (step 1). Then, the program computes the Conceptual Density of each concept in WordNet according to the senses it contains in its subhierarchy (step 2). It selects the concept c with highest density (step 3) and selects the senses below it as the correct senses for the respective words (step 4). If a word from W:

• has a single sense under c, it has already been disambiguated.

• has not such a sense, it is still ambiguous.

• has more than one such senses, we can eliminate all the other senses of w, but have not yet completely disambiguated w.

The algorithm proceeds then to compute the density for the remaining senses in the lattice, and continues to disambiguate words in W (back to steps 2, 3 and 4). When no further disambiguation is possible, the senses left for w are processed and the result is presented (step 5). To illustrate the process, consider the following text extracted from SemCor:

> *The <u>jury</u>(2) praised the <u>administration</u>(3) and <u>operation</u>(8) of the Atlanta <u>Police_Department</u>(1), the Fulton_Tax_Commissioner_'s_Office, the Bellwood and Alpharetta <u>prison_farms</u>(1), Grady_Hospital and the Fulton_Health_Department.*

Figure 3: sample sentence from SemCor

The underlined words are nouns represented in WordNet with the number of senses between brackets. The noun to be disambiguated in our example is *<u>operation</u>*., and a window size of five will be used.

(step 1) The following figure shows partially the lattice for the example sentence. As far as *<u>Prison_farm</u>* appears in a different hierarchy we do not show it in figure 4:

```
police_department_0
   => local department, department of
      local government
      => government department
         => department
         jury_1, panel
            => committee, commission
         operation_3, function
            => division
               => administrative unit
                  => unit
                     => organization
                        => social group
                           => people
                              => group

administration_1, governance...
jury_2
   => body
      => people
         => group, grouping
```

Figure 4: partial lattice for the sample sentence

The concepts in WordNet are represented as lists of synonyms. Word senses to be disambiguated are shown in bold. Underlined concepts are those selected with highest Conceptual Density. Monosemic nouns have sense number 0.

(Step 2) <administrative_unit>, for instance, has underneath 3 senses to be disambiguated and a subhierarchy size of 96 and therefore gets a Conceptual Density of 0.256. Meanwhile, <body>, with 2 senses and subhierarchy size of 86, gets 0.062.

(Step 3) <administrative_unit>, being the concept with highest Conceptual Density is selected.

(Step 4) **Operation_3**, **police_department_0** and **jury_1** are the senses chosen for *operation*, *Police Department* and *jury*. All the other concepts below <administrative_unit> are marked so that they are no longer selected. Other senses of those words are deleted from the lattice e.g. **jury_2**. In the next loop of the algorithm <body> will have only one disambiguation-word below it, and therefore its density will be much lower. At this point the algorithm detects that further disambiguation is not possible, and quits the loop.

(Step 5) The algorithm has disambiguated **operation_3**, **police_department_0**, **jury_1** and **prison_farm_0** (because this word is monosemous in WordNet), but the word *administration* is still ambiguous. The output of the algorithm , thus, will be that the sense for *operation* in this context, i.e. for this window, is **operation_3**. The disambiguation window will move rightwards, and the algorithm will try to disambiguate *Police Department* taking as context *administration*, *operation*, *prison farms* and whichever noun is first in the next sentence.

The disambiguation algorithm has and intermediate outcome between completely disambiguating a word or failing to do so. In some cases the algorithm returns several possible senses for a word. In this experiment we treat this cases as failure to disambiguate.

5 The Experiment

We selected one text from SemCor at random: br-a01 from the gender "Press: Reportage". This text is 2079 words long, and contains 564 nouns. Out of these, 100 were not found in WordNet. From the 464 nouns in WordNet, 149 are monosemous (32%).

The text plays both the role of input file (without semantic tags) and (tagged) test file. When it is treated as input file, we throw away all non-noun words, only leaving the lemmas of the nouns present in WordNet. The program does not face syntactic ambiguity, as the disambiguated part of speech information is in the input file. Multiple word entries are also available in the input file, as long as they are present in WordNet. Proper nouns have a similar treatment: we only consider those that can be found in WordNet. Figure 5 shows the way the algorithm would input the example sentence in figure 3 after stripping non-noun words.

After erasing the irrelevant information we get the words shown in figure 6[2].

The algorithm then produces a file with sense tags that can be compared automatically with the original file (c.f. figure 5).

```
<s>
<wd>jury</wd><sn>[noun.group.0]</sn><tag>NN</tag>
<wd>administration</wd><sn>[noun.act.0]</sn><tag>NN</tag>
<wd>operation</wd><sn>[noun.state.0]</sn><tag>NN</tag>
<wd>Police_Department</wd><sn>[noun.group.0]</sn><tag>NN</tag>
<wd>prison_farms</wd><mwd>prison_farm</mwd><msn>[noun.artifact.0]</msn><tag>NN</tag>
</s>
```

Figure 5: Semcor format

```
jury administration operation Police_Department prison_farm
```

Figure 6: input words

[2] *Note that we already have the knowledge that police department and prison farm are compound nouns, and that the lemma of prison farms is prison farm.*

Deciding the optimum context size for disambiguating using Conceptual Density is an important issue. One could assume that the more context there is, the better the disambiguation results would be. Our experiment shows that precision[3] increases for bigger windows, until it reaches window size 15, where it gets stabilised to start decreasing for sizes bigger than 25 (c.f. figure 7). Coverage over polysemous nouns behaves similarly, but with a more significant improvement. It tends to get its maximum over 80%, decreasing for window sizes bigger than 20.

Precision is given in terms of polysemous nouns only. The graphs are drawn against the size of the context[4] that was taken into account when disambiguating.

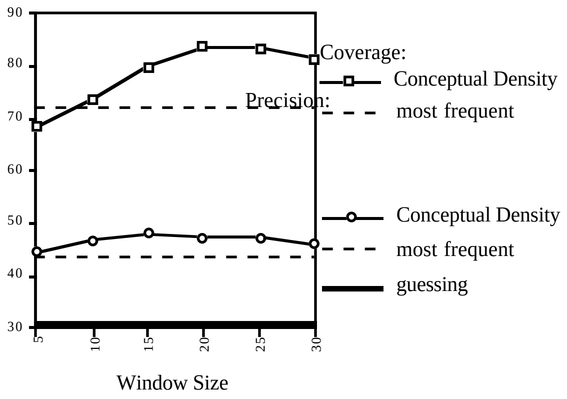

Figure 7: precision and coverage

Figure 7 also shows the guessing baseline, given when selecting senses at random. First, it was calculated analytically using the polysemy counts for the file, which gave 30% of precision. This result was checked experimentally running an algorithm ten times over the file, which confirmed the previous result.

We also compare the performance of our algorithm with that of the "most frequent" heuristic. The frequency counts for each sense were collected using the rest of SemCor, and then applied to the text. While the precision is similar to that of our algorithm, the coverage is nearly 10% worse.

All the data for the best window size can be seen in table 1. The precision and coverage shown in the preceding graph was for polysemous nouns only. If we also include monosemic nouns precision raises from 47.3% to 66.4%, and the coverage increases from 83.2% to 88.6%.

% w=25	Cover.	Prec.	Recall
polysemic	83.2	47.3	39.4
overall	88.6	66.4	58.8

Table 1: overall data for the best window size

6 Further Work

Senses in WordNet are organised in lexicographic files which can be roughly taken also as a semantic classification. If the senses of a given word that are from the same lexicographic file were collapsed, we would disambiguate at a level closer to the homograph level of disambiguation.

Another possibility we are currently considering is the inclusion of meronymic relations in the Semantic Density algorithm. The more semantic information the algorithm gathers the better performance it can be expected.

At the moment of writing this paper more extensive experiments which include other three texts from SemCor are under way. With these experiments we would like to evaluate the two improvements outlined above. Moreover, we would like to check the performance of other algorithms for conceptual distance on the same set of texts.

This methodology has been also used for disambiguating nominal entries of bilingual MRDs against WordNet (Rigau & Agirre 95).

7 Conclusion

The automatic method for the disambiguation of nouns presented in this paper is ready-usable in any general domain and on free-running text, given part of speech tags. It does not need any training and uses word sense tags from WordNet, an extensively used lexical data base.

---

[3] *Precision is defined as the ratio between correctly disambiguated senses and total number of answered senses. Coverage is given by the ratio between total number of answered senses and total number of senses. Recall is defined as the ratio between correctly disambiguated senses and total number of senses.*

[4] *Context size is given in terms of nouns.*

The algorithm is theoretically motivated and founded, and offers a general measure of the semantic relatedness for any number of nouns in a text.

In the experiment, the algorithm disambiguated one text (2079 words long) of SemCor, a subset of the Brown corpus. The results were obtained automatically comparing the tags in SemCor with those computed by the algorithm, which would allow the comparison with other disambiguation methods.

The results are promising, considering the difficulty of the task (free running text, large number of senses per word in WordNet), and the lack of any discourse structure of the texts.

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Word Sense Disambiguation using Conceptual Density

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Abstract.

This paper presents a method for the resolution of lexical ambiguity of nouns and its automatic evaluation over the Brown Corpus. The method relies on the use of the wide-coverage noun taxonomy of WordNet and the notion of conceptual distance among concepts, captured by a Conceptual Density formula developed for this purpose. This fully automatic method requires no hand coding of lexical entries, hand tagging of text nor any kind of training process. The results of the experiments have been automatically evaluated against SemCor, the sense-tagged version of the Brown Corpus.

1 Introduction

Much of recent work in lexical ambiguity resolution offers the prospect that a disambiguation system might be able to receive as input unrestricted text and tag each word with the most likely sense with fairly reasonable accuracy and efficiency. The most extended approach use the context of the word to be disambiguated together with information about each of its word senses to solve this problem.

Interesting experiments have been performed in recent years using preexisting lexical knowledge resources: [Cowie et al. 92], [Wilks et al. 93] with LDOCE, [Yarowsky 92] with Roget's International Thesaurus, and [Sussna 93], [Voorhees 93], [Richardson et al. 94], [Resnik 95] with WordNet.

Although each of these techniques looks promising for disambiguation, either they have been only applied to a small number of words, a few sentences or not in a public domain corpus. For this reason we have tried to disambiguate all the nouns from real texts in the public domain sense tagged version of the Brown corpus [Francis & Kucera 67], [Miller et al. 93], also called Semantic Concordance or SemCor for short[1]. The words in SemCor are tagged with word senses from WordNet, a broad semantic taxonomy for English [Miller 90][2]. Thus, SemCor provides an appropriate environment for testing our procedures and comparing among alternatives in a fully automatic way.

The automatic decision procedure for lexical ambiguity resolution presented in this paper is based on an elaboration of the conceptual distance among concepts: Conceptual Density [Agirre & Rigau 95]. The system needs to know how words are clustered in semantic classes, and how semantic classes are hierarchically organised. For this purpose, we have used WordNet. Our system tries to resolve the lexical ambiguity of nouns by finding the combination of senses from a set of contiguous nouns that maximises the Conceptual Density among senses.

The performance of the procedure was tested on four SemCor texts chosen at random. For comparison purposes two other approaches, [Sussna 93] and [Yarowsky 92], were also tried. The results show that our algorithm performs better on the test set.

Following this short introduction the Conceptual Density formula is presented. The main procedure to resolve lexical ambiguity of nouns using Conceptual Density is sketched on section 3. Section 4 describes extensively the experiments and its results. Finally, sections 5 and 6 deal with further work and conclusions.

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[1] Semcor comprises approximately 250,000 words. The tagging was done manually, and the error rate measured by the authors is around 10% for polysemous words.

[2] The senses of a word are represented by synonym sets (or synsets), one for each word sense. The nominal part of WordNet can be viewed as a tangled hierarchy of hypo/hypernymy relations among synsets. Nominal relations include also three kinds of meronymic relations, which can be paraphrased as member-of, made-of and component-part-of. The version used in this work is WordNet 1.4, The coverage in WordNet of senses for open-class words in SemCor reaches 96% according to the authors.

2 Conceptual Density and Word Sense Disambiguation

Conceptual distance tries to provide a basis for measuring closeness in meaning among words, taking as reference a structured hierarchical net. Conceptual distance between two concepts is defined in [Rada et al. 89] as the length of the shortest path that connects the concepts in a hierarchical semantic net. In a similar approach, [Sussna 93] employs the notion of conceptual distance between network nodes in order to improve precision during document indexing. [Resnik 95] captures semantic similarity (closely related to conceptual distance) by means of the information content of the concepts in a hierarchical net. In general these approaches focus on nouns.

The measure of conceptual distance among concepts we are looking for should be sensitive to:

• the length of the shortest path that connects the concepts involved.

• the depth in the hierarchy: concepts in a deeper part of the hierarchy should be ranked closer.

• the density of concepts in the hierarchy: concepts in a dense part of the hierarchy are relatively closer than those in a more sparse region.

• the measure should be independent of the number of concepts we are measuring.

We have experimented with several formulas that follow the four criteria presented above. The experiments reported here were performed using the Conceptual Density formula [Agirre & Rigau 95], which compares areas of subhierarchies.

To illustrate how Conceptual Density can help to disambiguate a word, in figure 1 the word W has four senses and several context words. Each sense of the words belongs to a subhierarchy of WordNet. The dots in the subhierarchies represent the senses of either the word to be disambiguated (W) or the words in the context. Conceptual Density will yield the highest density for the subhierarchy containing more senses of those, relative to the total amount of senses in the subhierarchy. The sense of W contained in the subhierarchy with highest Conceptual Density will be chosen as the sense disambiguating W in the given context. In figure 1, sense2 would be chosen.

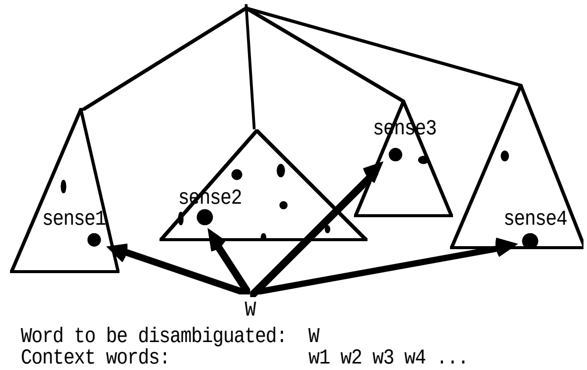

Figure 1: senses of a word in WordNet

Given a concept *c*, at the top of a subhierarchy, and given *nhyp* (mean number of hyponyms per node), the Conceptual Density for *c* when its subhierarchy contains a number *m* (marks) of senses of the words to disambiguate is given by the formula below:

$$CD(c,m) = \frac{\sum_{i=0}^{m-1} nhyp^{i^{0.20}}}{descendants_c} \qquad \textbf{(1)}$$

Formula 1 shows a parameter that was computed experimentally. The 0.20 tries to smooth the exponential *i*, as *m* ranges between 1 and the total number of senses in WordNet. Several values were tried for the parameter, and it was found that the best performance was attained consistently when the parameter was near 0.20.

3 The Disambiguation Algorithm Using Conceptual Density

Given a window size, the program moves the window one noun at a time from the beginning of the document towards its end, disambiguating in each step the noun in the middle of the window and considering the other nouns in the window as context. Non-noun words are not taken into account.

The algorithm to disambiguate a given noun w in the middle of a window of nouns W (c.f. figure 2) roughly proceeds as follows:

```
(Step 1) tree := compute_tree(words_in_window)
         loop
(Step 2)   tree := compute_conceptual_distance(tree)
(Step 3)   concept := selecct_concept_with_highest_weigth(tree)
           if  concept = null then exitloop
(Step 4)   tree := mark_disambiguated_senses(tree,concept)
         endloop
(Step 5) output_disambiguation_result(tree)
```

Figure 2: algorithm for each window

First, the algorithm represents in a lattice the nouns present in the window, their senses and hypernyms (step 1). Then, the program computes the Conceptual Density of each concept in WordNet according to the senses it contains in its subhierarchy (step 2). It selects the concept c with highest Conceptual Density (step 3) and selects the senses below it as the correct senses for the respective words (step 4).

The algorithm proceeds then to compute the density for the remaining senses in the lattice, and continues to disambiguate the nouns left in W (back to steps 2, 3 and 4). When no further disambiguation is possible, the senses left for w are processed and the result is presented (step 5).

Besides completely disambiguating a word or failing to do so, in some cases the disambiguation algorithm returns several possible senses for a word. In the experiments we considered these partial outcomes as failure to disambiguate.

4 The Experiments

4.1 The texts

We selected four texts from SemCor at random: br-a01 (where a stands for gender "Press: Reportage"), br-b20 (b for "Press: Editorial"), br-j09 (j means "Learned: Science") and br-r05 (r for "Humour"). Table 1 shows some statistics for each text.

text	words	nouns	nouns in WN	monosemous
br-a01	2079	564	464	149 (32%)
br-ab20	2153	453	377	128 (34%)
br-j09	2495	620	586	205 (34%)
br-r05	2407	457	431	120 (27%)
total	9134	2094	1858	602 (32%)

Table 1: data for each text

An average of 11% of all nouns in these four texts were not found in WordNet. According to this data, the amount of monosemous nouns in these texts is bigger (32% average) than the one calculated for the open-class words from the whole SemCor (27.2% according to [Miller et al. 94]).

For our experiments, these texts play both the role of input files (without semantic tags) and (tagged) test files. When they are treated as input files, we throw away all non-noun words, only leaving the lemmas of the nouns present in WordNet.

4.2 Results and evaluation

One of the goals of the experiments was to decide among different variants of the Conceptual Density formula. Results are given averaging the results of the four files. Partial disambiguation is treated as failure to disambiguate. Precision (that is, the percentage of actual answers which were correct) and recall (that is, the percentage of possible answers which were correct) are given in terms of polysemous nouns only. Graphs are drawn against the size of the context[3] .

• **meronymy does not improve performance as expected.** A priori, the more relations are taken in account (e.i. meronymic relations, in addition to the hypo/hypernymy relation) the better density would capture semantic relatedness, and therefore better results can be expected.

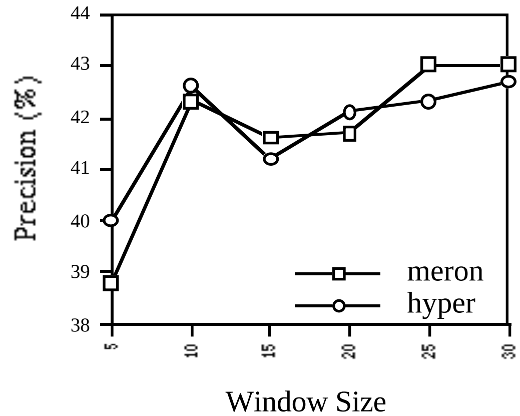

Figure 3: meronymy and hyperonymy

The experiments (see figure 3) showed that there is not much difference; adding meronymic information does not improve precision, and raises coverage only 3% (approximately). Nevertheless, in the rest of the results reported below, meronymy and hypernymy were used.

• **global nhyp is as good as local nhyp.** The average number of hyponyms or *nhyp* (c.f. formula 1) can be approximated in two ways. If an independent *nhyp* is computed for every concept in WordNet we call it *local nhyp*. If instead, a unique *nhyp* is computed using the whole hierarchy, we have *global nhyp*.

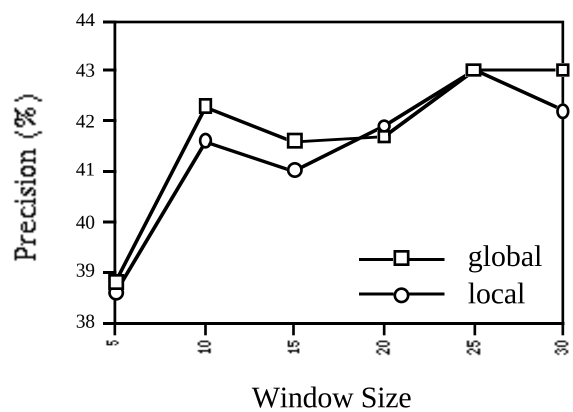

Figure 4: *local nhyp* vs. *global nhyp*

[3]context size is given in terms of nouns.

While *local nhyp* is the actual average for a given concept, *global nhyp* gives only an estimation. The results (c.f. figure 4) show that *local nhyp* performs only slightly better. Therefore *global nhyp* is favoured and was used in subsequent experiments.

• **context size: different behaviour for each text.** One could assume that the more context there is, the better the disambiguation results would be. Our experiments show that each file from SemCor has a different behaviour (c.f. figure 5) while br-b20 shows clear improvement for bigger window sizes, br-r05 gets a local maximum at a 10 size window, etc.

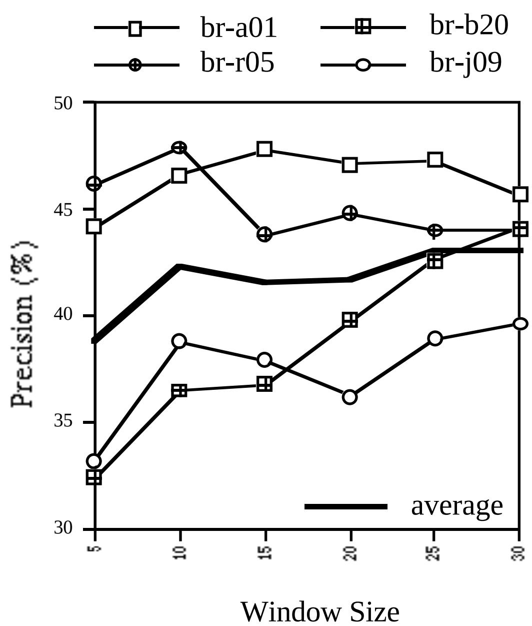

Figure 5: context size and different files

As each text is structured a list of sentences, lacking any indication of headings, sections, paragraph endings, text changes, etc. the program gathers the context without knowing whether the nouns actually occur in coherent pieces of text. This could account for the fact that in br-r05, composed mainly by short pieces of dialogues, the best results are for window size 10, the average size of this dialogue pieces. Likewise, the results for br-a01, which contains short journalistic texts, are best for window sizes from 15 to 25, decreasing significatly for size 30.

In addition, the actual nature of each text is for sure an important factor, difficult to measure, which could account for the different behavoiur on its own. In order to give an overall view of the performance, we consider the average behaviour.

• **file vs. sense.** WordNet groups noun senses in 24 lexicographer's files. The algorithm assigns a noun both an specific sense and a file label. Both file matches and sense matches are interesting to count. While the sense level gives a fine graded measure of the algorithm, the file level gives an indication of the performance if we were interested in a less sharp level of disambiguation. The granularity of the sense distinctions made in [Hearst, 91], [Yarowsky 92] and [Gale et al. 93] also called homographs in [Guthrie et al. 93], can be compared to that of the file level in WordNet.

For instance, in [Yarowsky 92] two homographs of the noun *bass* are considered, one characterised as MUSIC and the other as ANIMAL, INSECT. In WordNet, the 6 senses of *bass* related to music appear in the following files: ARTIFACT, ATTRIBUTE, COMMUNICATION and PERSON. The 3 senses related to animals appear in the files ANIMAL and FOOD. This means that while the homograph level in [Yarowsky 92] distinguishes two sets of senses, the file level in WordNet distinguishes six sets of senses, still finer in granularity.

Figure 6 shows that, as expected, file-level matches attain better performance (71.2% overall and 53.9% for polysemic nouns) than sense-level matches.

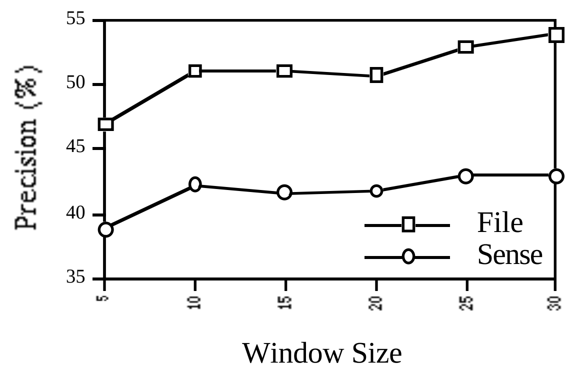

Figure 6: sense level vs. file level

• **evaluation of the results** Figure 7 shows that, overall, coverage over polysemous nouns increases significantly with the window size, without losing precision. Coverage tends to get stabilised near 80%, getting little improvement for window sizes bigger than 20.

The figure also shows the guessing baseline, given by selecting senses at random. This baseline was first calculated analytically and later checked experimentally. We also compare the performance of our algorithm with that of the "most frequent" heuristic. The frequency counts for each sense were collected using the rest of SemCor, and then applied to the four texts. While the precision is similar to that of our algorithm, the coverage is 8% worse.

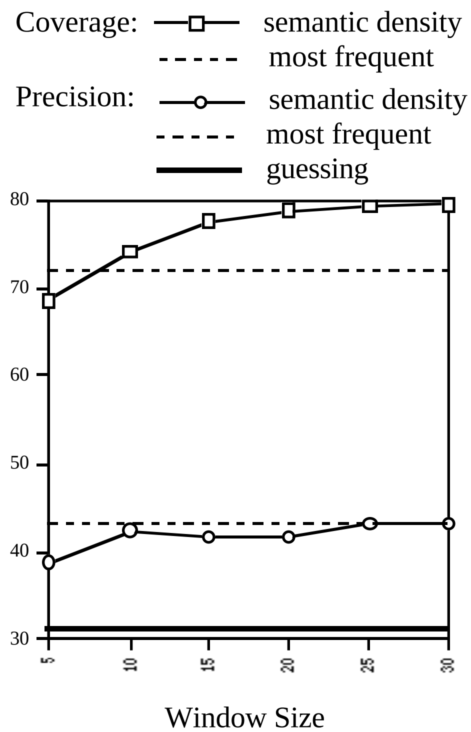

Figure 7: precision and coverage

All the data for the best window size can be seen in table 2. The precision and coverage shown in all the preceding graphs were relative to the polysemous nouns only. Including monosemic nouns precision raises, as shown in table 2, from 43% to 64.5%, and the coverage increases from 79.6% to 86.2%.

%	w=30	Cover.	Prec.	Recall
overall	File	86.2	71.2	61.4
	Sense		64.5	55.5
polysemic	File	79.6	53.9	42.8
	Sense		43	34.2

Table 2: overall data for the best window size

4.3 Comparison with other works

The raw results presented here seem to be poor when compared to those shown in [Hearst 91], [Gale et al. 93] and [Yarowsky 92]. We think that several factors make the comparison difficult. Most of those works focus in a selected set of a few words, generally with a couple of senses of very different meaning (coarse-grained distinctions), and for which their algorithm could gather enough evidence. On the contrary, we tested our method with **all** the nouns in a subset of an unrestricted public domain corpus (more than 9.000 words), making fine-grained distinctions among all the senses in WordNet.

An approach that uses hierarchical knowledge is that of [Resnik 95], which additionally uses the information content of each concept gathered from corpora. Unfortunately he applies his method on a different task, that of disambiguating sets of related nouns. The evaluation is done on a set of related nouns from Roget's Thesaurus tagged by hand. The fact that some senses were discarded because the human judged them not reliable makes comparison even more difficult.

In order to compare our approach we decided to implement [Yarowsky 92] and [Sussna 93], and test them on our texts. For [Yarowsky 92] we had to adapt it to work with WordNet. His method relies on cooccurrence data gathered on Roget's Thesaurus semantic categories. Instead, on our experiment we use saliency values[4] based on the lexicographic file tags in SemCor. The results for a window size of 50 nouns are those shown in table 3[5]. The precision attained by our algorithm is higher. To compare figures better consider the results in table 4, were the coverage of our algorithm was easily extended using the version presented below, increasing recall to 70.1%.

%	Cover.	Prec.	Recall
C.Density	86.2	71.2	61.4
Yarowsky	100.0	64.0	64.0

Table 3: comparison with [Yarowsky 92]

From the methods based on Conceptual Distance, [Sussna 93] is the most similar to ours. Sussna disambiguates several documents from a public corpus using WordNet. The test set was tagged by hand, allowing more than one correct senses for a single word. The method he uses has to overcome a combinatorial explosion[6] controlling the size of the window and “freezing” the senses for all the nouns preceding the noun to be disambiguated. In order to freeze the winning sense Sussna's algorithm is forced to make a unique choice. When Conceptual Distance is not able to choose a single sense, the algorithm chooses one at random.

Conceptual Density overcomes the combinatorial explosion extending the notion of conceptual distance from a pair of words to n words, and therefore can yield more than one correct sense for a word. For comparison, we altered our algorithm to also make random choices when unable to choose a single sense. We applied the algorithm Sussna considers best,

[4]We tried both mutual information and association ratio, and the later performed better.

[5]The results of our algorithm are those for window size 30, file matches and overall.

[6]In our replication of his experiment the mutual constraint for the first 10 nouns (the optimal window size according to his experiments) of file br-r05 had to deal with more than 200,000 synset pairs.

discarding the factors that do not affect performance significantly[7], and obtain the results in table 4.

%		Cover.	Prec.
C.Density	File	100.0	70.1
	Sense		60.1
Sussna	File	100.0	64.5
	Sense		52.3

Table 4: comparison with [Sussna 93]

A more thorough comparison with these methods could be desirable, but not possible in this paper for the sake of conciseness.

5 Further Work

We would like to have included in this paper a study on whether there is or not a correlation among correct and erroneous sense assignations and the degree of Conceptual Density, that is, the actual figure held by formula 1. If this was the case, the error rate could be further decreased setting a certain threshold for Conceptual Density values of winning senses. We would also like to evaluate the usefulness of partial disambiguation: decrease of ambiguity, number of times correct sense is among the chosen ones, etc.

There are some factors that could raise the performance of our algorithm:

• **Work on coherent chunks of text.** Unfortunately any information about discourse structure is absent in SemCor, apart from sentence endings The performance would gain from the fact that sentences from unrelated topics would not be considered in the disambiguation window.

• **Extend and improve the semantic data.** WordNet provides sinonymy, hypernymy and meronyny relations for nouns, but other relations are missing. For instance, WordNet lacks cross-categorial semantic relations, which could be very useful to extend the notion of Conceptual Density of nouns to Conceptual Density of words. Apart from extending the disambiguation to verbs, adjectives and adverbs, cross-categorial relations would allow to capture better the relations among senses and provide firmer grounds for disambiguating.

These other relations could be extracted from other knowledge sources, both corpus-based or MRD-based. If those relations could be given on WordNet senses, Conceptual Density could profit from them. It is our belief, following the ideas of [McRoy 92] that full-fledged lexical ambiguity resolution should combine several information sources. Conceptual Density might be only one of a number of complementary evidences of the plausibility of a certain word sense.

Furthermore, WordNet 1.4 is not a complete lexical database (current version is 1.5).

• **Tune the sense distinctions to the level best suited for the application.** On the one hand the sense distinctions made by WordNet 1.4 are not always satisfactory. On the other hand, our algorithm is not designed to work on the file level, e.g. if the sense level is unable to distinguish among two senses, the file level also fails, even if both senses were from the same file. If the senses were collapsed at the file level, the coverage and precision of the algorithm at the file level might be even better.

6 Conclusion

The automatic method for the disambiguation of nouns presented in this paper is ready-usable in any general domain and on free-running text, given part of speech tags. It does not need any training and uses word sense tags from WordNet, an extensively used lexical data base.

Conceptual Density has been used for other tasks apart from the disambiguation of free-running test. Its application for automatic spelling correction is outlined in [Agirre et al. 94]. It was also used on Computational Lexicography, enriching dictionary senses with semantic tags extracted from WordNet [Rigau 94], or linking bilingual dictionaries to WordNet [Rigau and Agirre 96].

In the experiments, the algorithm disambiguated four texts (about 10,000 words long) of SemCor, a subset of the Brown corpus. The results were obtained automatically comparing the tags in SemCor with those computed by the algorithm, which would allow the comparison with other disambiguation methods. Two other methods, [Sussna 93] and [Yarowsky 92], were also tried on the same texts, showing that our algorithm performs better.

Results are promising, considering the difficulty of the task (free running text, large number of senses per word in WordNet), and the lack of any discourse structure of the texts. Two types of results can be obtained: the specific sense or a coarser, file level, tag.

Acknowledgements

This work, partially described in [Agirre &Rigau 96], was started in the Computing Research Laboratory in New Mexico State University. We wish to thank all the staff of the CRL and specially Jim Cowie, Joe Guthrie, Louise Guthrie and David Farwell. We would also like to thank Xabier Arregi, Jose mari Arriola, Xabier Artola, Arantza Díaz de Ilarraza, Kepa Sarasola and Aitor Soroa from the Computer Science Faculty of EHU and Francesc Ribas, Horacio Rodríguez and Alicia Ageno from the Computer Science Department of UPC.

[7] Initial mutual constraint size is 10 and window size is 41. Meronymic links are also considered. All the links have the same weigth.

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• Compute the upper bound of this method using WordNet.

How correct this methodology can be? That is, words belonging to the same narrow context in SemCor can represent distant correct concepts in WordNet (having other incorrect ones closer).

7 Conclusion

The automatic method for the disambiguation of nouns presented in this paper is ready to use in any general domain, free-running text, given part of speech tags. It does not need any training and uses word sense tags from WordNet, a widely used lexical data base. The algorithm is theoretically motivated, and offers a general measure of the semantic relatedness for any number of nouns.

Conceptual Density has been used for other tasks apart from the disambiguation of free-running test. Its application for automatic spelling correction is outlined in [Agirre et al. 94]. It was also used on Computational Lexicography, enriching dictionary senses with semantic tags extracted from WordNet [Rigau 94], or linking bilingual dictionaries to WordNet [Rigau and Agirre 95].

In the experiments, the algorithm disambiguated four texts (more than 9,000 words long) of SemCor, a subset of the Brown corpus. The results were obtained automatically by comparing the tags in SemCor with those computed by the algorithm. This allows the comparison with other disambiguation methods. Two other methods, [Sussna 93] and [Yarowsky 92], were also tried on the same texts, showing that our algorithm performs better.

The results are promising, considering the difficulty of the task (free running text, large number of senses per word in WordNet), and the lack of any discourse structure of the texts. Two kinds of results can be obtained: the specific sense or a coarser, file level, tag.

Acknowledgements

We wish to thank all the staff of the CRL and specially Jim Cowie, Joe Guthtrie, Louise Guthrie and David Farwell. We would also like to thank Ander Murua, who provided mathematical assistance, Xabier Arregi, Jose Mari Arriola, Xabier Artola, Arantxa Diaz de Ilarraza, Kepa Sarasola, and Aitor Soroa from the Computer Science Department of EHU and Francesc Ribas, Horacio Rodríguez and Alicia Ageno from the Computer Science Department of UPC.

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%		Cover.	Prec.
C.Density	File	100.0	70.1
	Sense		60.1
Sussna	File	100.0	64.5
	Sense		52.3

Table 4: comparison with [Sussna 93]

6 Future Work

Initially, we would like to carry out a study on whether there is or is not a correlation between correct and erroneous sense assignations and the degree of Conceptual Density computed by formula 3. If this was the case, the error rate could be further decreased by setting a certain threshold for Conceptual Density values for winning senses.

There are other factors that could increase the performance of our algorithm:

• Work on coherent chunks of text.

Unfortunately any information about discourse structure is absent in SemCor, apart from sentence endings. If coherent pieces of discourse were taken as input, both performance and efficiency of the algorithm might improve. The performance would gain from the fact that sentences from unrelated topics would not be considered in the disambiguation window. We think that efficiency could also be improved if the algorithm worked on entire coherent chunks instead of one word at a time.

• Extend and improve the semantic data.

WordNet lacks cross-categorial semantic relations, which could be very useful for extending the notion of Conceptual Density of nouns to Conceptual Density of words. Apart from extending disambiguation to verbs, adjectives and adverbs, cross-categorial relations would allow the algorithm better capture the relations among senses and provide firmer grounds for disambiguating.

If Conceptual Density takes into account global relations among words, it may be advantageous to combine it with other sources of knowledge (both corpus-based or MRD-based) such as syntactic cues, word frequencies, collocations, selectional restrictions [Yarowsky 93], [Ribas 95], and so on. (c.f. [McRoy 92]). For instance, [Richardson et al. 94] defines conceptual similarity between two senses based on WordNet and informational measures taken from corpora, but does not give any evaluation of their method.

• Tune the sense distinctions to the level best suited for the application.

On the one hand, the sense distinctions made by WordNet 1.4 are not always satisfactory and, obviously, WordNet 1.4 is not a complete lexical Database. For instance, the three senses of abobe and the lack of connections among them, which are fixed up in WordNet 1.5. On the other hand, our algorithm is not designed to work on the file level, e.g. if the sense level is unable to distinguish among two senses, the file level also fails, even if both senses were from the same file. If the senses were collapsed at the file level, the coverage and precision of the algorithm at the file level might be better.

12.*Initial mutual constraint size is 10 and window size is 41. Meronymic links are also considered. All the links have the same weigth.*

The raw results presented here seem to be poor when compared to those shown in [Hearst 91], [Gale et al. 93] and [Yarowsky 92]. We think that several factors make the comparison difficult. Most of those works focus on a selected set of a few words, generally with a couple of senses of very different meaning (coarse-grained distinctions), and for which their algorithm could gather enough evidence. On the contrary, we tested our method with **all** the nouns in a subset of an unrestricted public domain corpus (more than 9.000 words), making fine-grained distinctions among all the senses in WordNet.

[Guthrie et al. 93] tested their method in similar conditions to ours, but without performing an extensive and automatic testing. The results reported there seem to be lower than those shown here. In an experiment with 50 sample sentences from LDOCE, 47% of the words were correctly disambiguated to the sense level, and 72% to the homograph level (our file level would stand between their homograph and sense levels).

An approach that uses hierarchical knowledge is that of [Resnik 95], which additionally uses the information content of each concept gathered from corpora. Unfortunately he applies his method on a different task, that of disambiguating sets of related nouns. The evaluation is done on a set of related nouns from Roget's Thesaurus tagged by hand. The fact that some senses were discarded because the human judged them not reliable makes comparison even more difficult.

In order to compare our approach we decided to implement [Yarowsky 92] and [Sussna 93], and test them on our texts. For [Yarowsky 92] we had to adapt it to work with WordNet. His method relies on cooccurrence data gathered on Roget's Thesaurus semantic categories. Instead, on our experiment we use saliency values[9] based on the lexicographic file tags in SemCor (see Figure 4). The results for a window size of 50 are those shown in table 3[10]. The precision attained by our algorithm is higher. To compare figures better consider the results in table 4, were the coverage of our algorithm was easily extended using the version presented below, increasing recall to 70.1%.

%	Cover.	Prec.	Recall
C.Density	86.2	71.2	61.4
Yarowsky	100.0	64.0	64.0

Table 3: comparison with [Yarowsky 92]

From the methods based on Conceptual Distance, [Sussna 93] is the most similar to ours. Sussna disambiguates several documents from a public corpus using WordNet. The test set was tagged by hand, allowing more than one correct senses for a single word. The method he uses has to overcome a combinatorial explosion[11] controlling the size of the window and “freezing” the senses for all the nouns preceding the noun to be disambiguated. In order to freeze the winning sense Sussna's algorithm is forced to make a unique choice. When Conceptual Distance is not able to choose a single sense, he has to choose one at random.

Conceptual Density overcomes the combinatorial explosion extending the notion of conceptual distance from a pair of words to n words, and therefore can yield more than one correct sense for a word. For comparison, we altered our algorithm to also make random choices when unable to choose a single sense. We applied the algorithm Sussna considers best, discarding the factors that do not affect performance significantly[12], and obtain the results in table 4.

9.*We tried both mutual information and association ratio, and the later performed better.*

10.*The results of our algorithm are those for window size 30, file matches and overall.*

11.*In our replication of his experiment the mutual constraint for the first 10 nouns (the optimal window size according to his experiments) of file br-r05 had to deal with more than 200.000 synset pairs.*

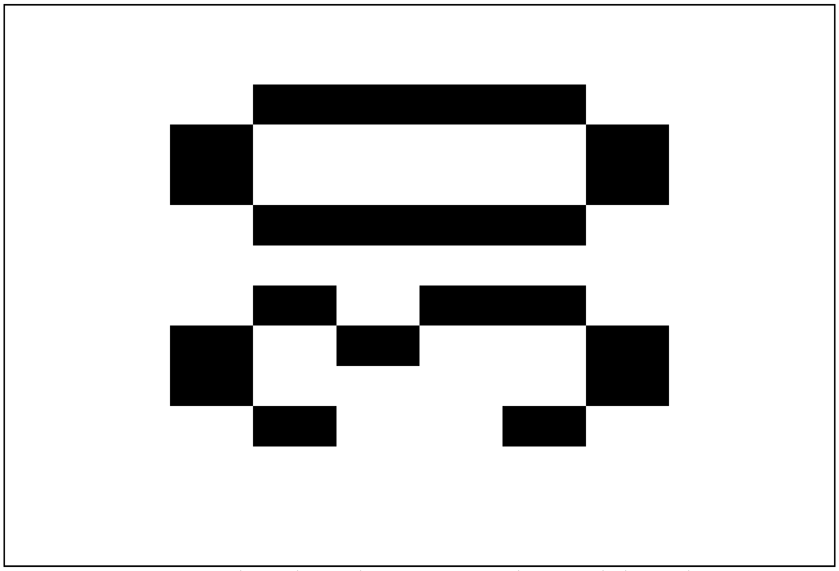

Figure 11: complete disambiguation and partial disambiguation

5.2.6 file vs. sense

WordNet synsets can be grouped by the lexicographic files they are coming from (e.g. `ACT, ANIMAL, FOOD,` etc.) Both file matches and synset matches are interesting to count. While the sense level gives a fine grained measure of the algorithm, the file level gives an indication of the performance if we were interested in a less precise level of disambiguation. The granularity of the sense distinctions made in [Hearst, 91], [Gale et al. 93] and [Yarowsky 92], also called homographs in [Guthrie et al. 93], can be compared to that of the file level in WordNet.

For instance, in [Yarowsky 92] two homographs of the noun `bass` are considered, one characterised as `MUSIC` and the other as `ANIMAL`, `INSECT`. In WordNet, the 6 senses of `bass` related to music appear in the following files: `ARTIFACT`, `ATTRIBUTE`, `COMMUNICATION` and `PERSON`. The 3 senses related to animals appear in the files `ANIMAL` and `FOOD`. This means that while the homograph level in [Yarowsky 92] distinguishes two sets of senses, the file level in WordNet distinguishes six sets of senses, still finer in granularity.

The following figure shows that, as expected, file-level matches attain better performance (71.2% overall and 53.9% for polysemic nouns) than sense-level matches.

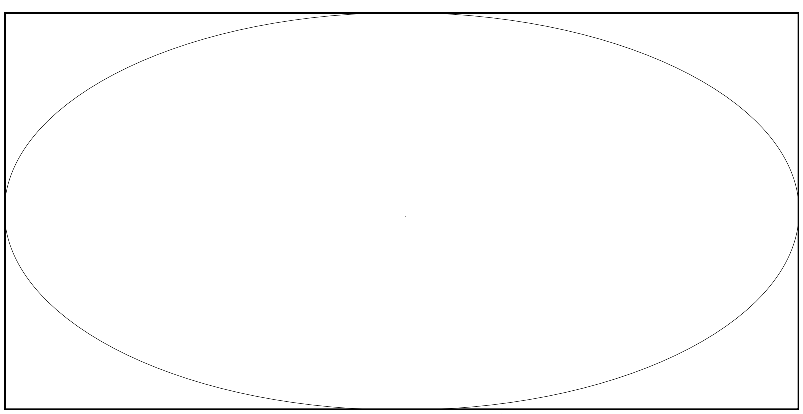

Figure 12: sense level v. file level

5.3 Comparison with other works

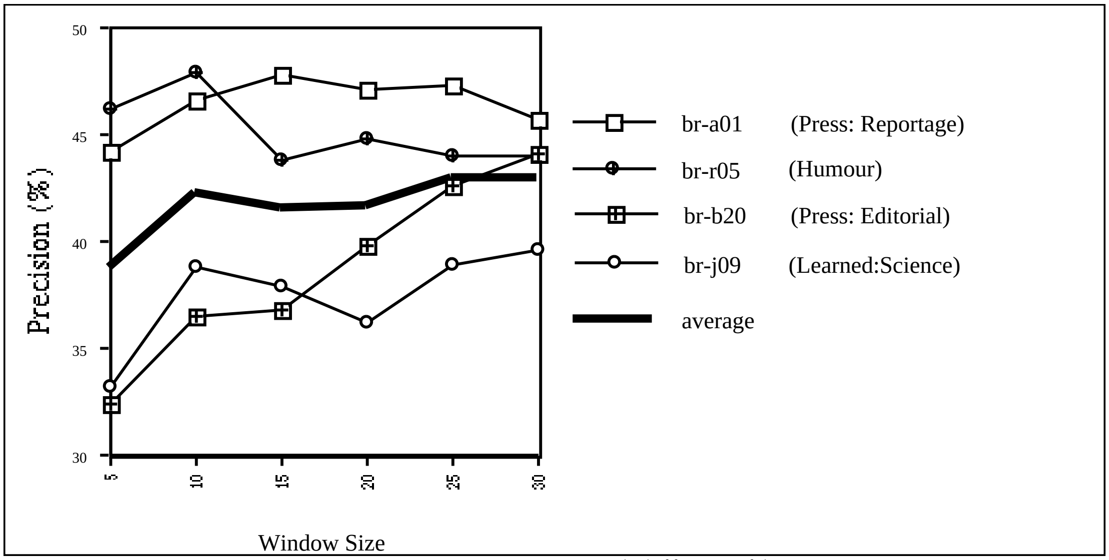

Figure 10: context size and different files

Each text is structured as a list of sentences, lacking any indication of headings, sections, paragraph endings, text changes, etc. This means that the program gathers the context without knowing whether the nouns actually occur in coherent pieces of text. This could account for the fact that in br-r05, composed mainly by short pieces of dialogues, the best results are for window size 10, the average size of pieces of this dialogue. Longer windows will include other pieces of unrelated dialogues that could cause the disambiguation process to go astray.

In addition, SemCor files can be composed of different pieces of unrelated texts without explicit indication. For instance, two of our test files (br-a01 and br-b20) are collections of short journalistic texts. This could explain why the performance of br-a01 decreases for windows of 30 nouns. For most nouns the context window would include nouns from other articles.

The polysemy level could also affect the performance, but in our texts less polysemy does not correlate with better performance. Nevertheless the actual nature of each text is certainly an important factor, difficult to measure, which could account for the different behaviour on its own. For instance, the poor performance on text br-j09 could be explained by its technical nature. Further analysis of the errors, contexts and relations found among the words would be needed to be more conclusive.

In order to give an overall view of the performance, we consider the average behaviour for formulating our conclusions leaving aside these considerations.

5.2.5 partial disambiguation

The disambiguation algorithm has an intermediate outcome between completely disambiguating a word or failing to do so. In some cases the algorithm just manages to discard some senses of the word, but can not choose a single sense. The automatic evaluation program does not take these cases into account, treating them as failures to disambiguate. While the number of words that are not disambiguated decreases for the benefit of completely disambiguated as the window size is bigger, the number of partially disambiguated words stays the same (see Figure 11).

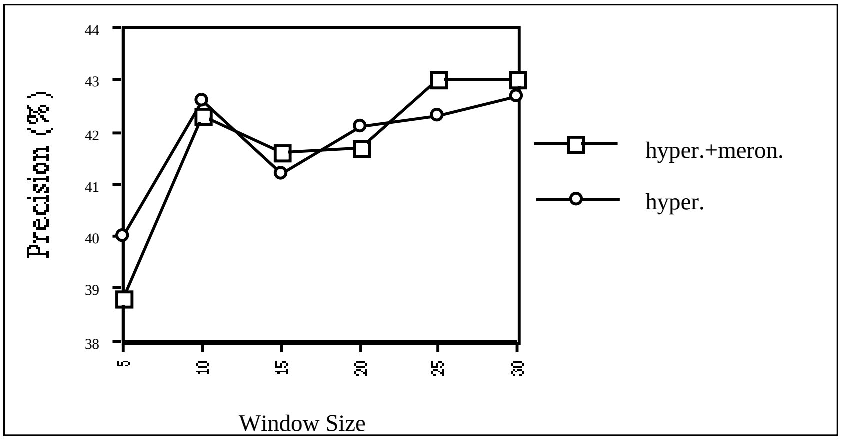

Figure 8: meronymy and hyperonymy

5.2.3 global nhyp is as good as local nhyp.

There was an aspect of the density formula which we could not decide analytically and which we wanted to check experimentally. It refers to the way *nhyp* is calculated (c.f. formula 2). If *nhyp* is computed using formula 2, we call it *local nhyp*, because it has to be computed for every concept of WordNet. Rather than using this *local nhyp*, it would be more desirable, specially for efficiency, if only one global *nhyp* were used for all the concepts. This *global nhyp* can be computed using the whole noun hierarchy. Depending on which *nhyp* is chosen will either be the real number of descendant senses for c (for local *nhyp*) or and estimation based on the global *nhyp*.

To decide whether using local *nhyp* or global *nhyp* affects the performance, we ran parallel experiments using both. The results (see Figure 9) show that there is only a slight difference between them. Therefore, *global nhyp* was used in the experiments.

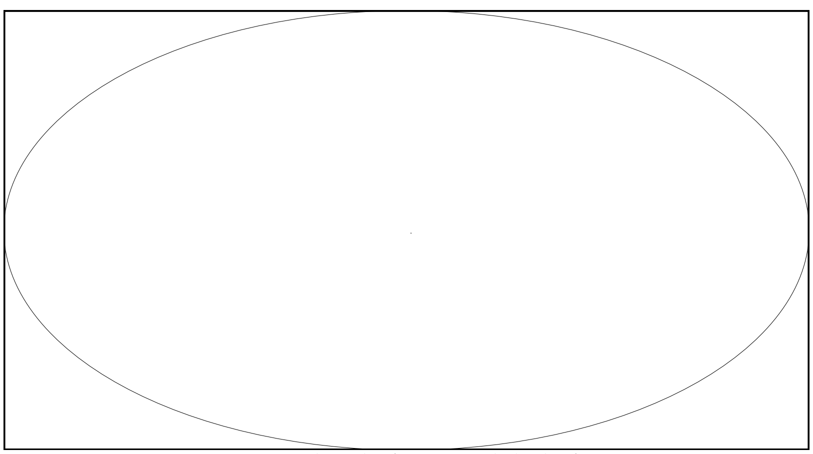
Figure 9: local *nhyp* vs. global *nhyp*

5.2.4 context size: different behaviour for each text

Deciding what context size was better for disambiguating using Conceptual Density is an important issue. One could assume that the more context there is, the better would be the disambiguation results. Our experiments show that each file from SemCor has a different behaviour (see Figure 10). While br-b20 shows clear improvement for bigger window sizes, br-r05 gets a local maximum at a size window of 10 nouns, etc.

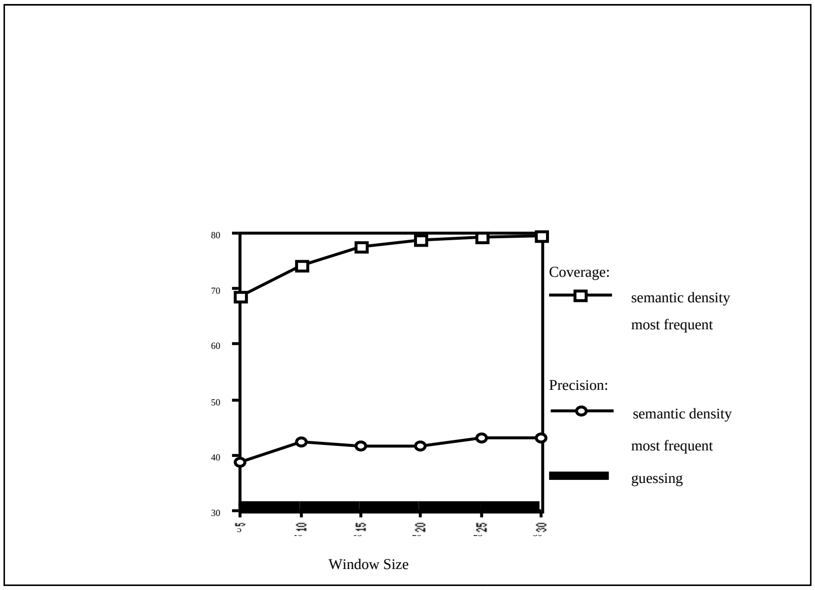

Figure 7: precision and coverage

The figure also shows the guessing baseline, given by selecting senses at random. First, it was calculated analytically using the polysemy counts for the files, which gave 30% of precision. This result was checked experimentally running an algorithm ten times over the files, which confirmed the previous result.

We also compare the performance of our algorithm with that of the most frequent heuristic. The frequency counts for each sense were collected using the rest of SemCor, and then apply the results to the four texts. While the precision is similar to that of our algorithm, the coverage is 8% worse.

All the data for the best window size can be seen in table 2.

%	w=30	Cover.	Prec.	Recall
overall	File	86.2	71.2	61.4
	Sense		64.5	55.5
polyse-mic	File	79.6	53.9	42.8
	Sense		43	34.2

Table 2: overall data for the best window size

The precision and coverage shown in all preceding plots were relative to the polysemous nouns only. If we also include monosemic nouns precision raises from 43% to 64.5%, and the coverage increases from 79.6% to 86.2%.

5.2.2 meronymy does not improve performance as expected.

One parameter controls whether meronymic relations, in addition to the hypo/hypernymy relation, are taken into account or not. In principle the more relations are taken in account, the better density would capture semantic relatedness and, therefore, the better the expected results. The experiments (see Figure 8) showed that there is not much difference; adding meronymic information does not improve precision, and raises coverage only 3% (approximately). Nevertheless, in the results reported, meronymy and hypernymy were used.

```
<wd>operation</wd><sn>[noun.state.0]</sn><tag>NN</tag>
```

```
<wd>Police_Department</wd><sn>[noun.group.0]</sn><tag>NN</tag>
```

```
<wd>prison_farms</wd><mwd>prison_farm</mwd><msn>[noun.arti-
fact.0]</msn>
    <tag>NN</tag>
```

```
</s>
```

Figure 5: Semcor format

After erasing the irrelevant information we get the following words[6]:

```
jury administration operation Police_Department
prison_farm
```

Figure 6: input words

The algorithm then produces a file with sense tags that can be compared automatically with the original file (see figure 5). An automatic program counts sense level matches and file level matches (see Section 5.2.6) for the three classes of results: complete disambiguation, partial disambiguation and failure to disambiguate. For the results shown in Section 5.2, partial disambiguation was considered as failure to disambiguate.

5.2 Results and evaluation

One of the goals of the experiments was to decide among different variants of the Conceptual Density formula. Results are given averaging the results of the four files. Partial disambiguation is treated as failure to disambiguate. Precision[7] is given in terms of polysemous nouns only. Plots are drawn against the size of the context[8] that was taken into account when disambiguating.

5.2.1 evaluation of the results

Figure 7 shows that, overall, coverage of polysemous nouns increases significantly with the window size, without losing precision. Coverage tends to stabilised near 80%, getting little improvement for window sizes bigger than 20.

6.*Note that in the input texts we already have the knowledge that police department and prison farm are compound nouns, and that the lemma of prison farms is prison farm.*
7.*Precision is defined as the ratio between correctly disambiguated senses and total number of answered senses. Coverage is given by the ratio between total number of answered senses and total number of senses. Recall is defined as the ratio between correctly disambiguated senses and the total number of senses.*
8.*context size is given in terms of nouns.*

procedure is repeated. At this point we start afresh with all senses of the words in the window.

Back in the example, the algorithm has disambiguated **`operation_3`**, **`police_department_0`**, **`jury_1`** and **`prison_farm_0`** (because this word is monosemous in WordNet), but the word *administration* is still ambiguous. The output of the algorithm , thus, will be that the sense for *operation* in this context, i.e. for this window, is **`operation_3`**. The disambiguation window will move rightwards, and the algorithm will try to disambiguate *Police_Department* taking as context *administration*, *operation*, *prison_farms* and whichever noun is first in the next sentence.

5 The Experiments

5.1 The texts

We selected four texts from SemCor at random: a press report (br-a01), an editorial (br-b20), a scientific text (br-j09) and a humorous article (br-r05). Table 1 shows some statistics for each text

text	words	nouns	nouns in WN	monosemous
br-a01	2079	564	464	149 (32%)
br-b20	2153	453	377	128 (34%)
br-j09	2495	620	586	205 (34%)
br-r05	2407	457	431	120 (27%)
total	9134	2094	1858	602 (32%)

Table 1

An average of 11% of all the nouns in these four texts were not found in WordNet. According to this data, the percentage of monosemous nouns in these texts is bigger (32% average) than the one calculated for the open-class words from the whole SemCor (27.2% according to [Miller et al. 94]). [Sussna 93] presents a similar degree of polysemy for nouns (34% of monosemous nouns), but in a different text collection.

These texts play both the role of input files (without semantic tags) and (tagged) test files. When they are treated as input files, we throw away all non-noun words, only leaving the lemmas of the nouns present in WordNet. The program does not deal with syntactic ambiguity, as the part of speech information is in the input files. Multiple word entries are also available in the input files, as long as they are present in WordNet. Proper nouns have a similar treatment: we only consider those that can be found in WordNet. Figure 5 shows the way the algorithm would input the example sentence in figure 3 after stripping non-noun words:

```
<s>

<wd>jury</wd><sn>[noun.group.0]</sn><tag>NN</tag>

<wd>administration</wd><sn>[noun.act.0]</sn><tag>NN</tag>
```

administration_1, governance, government, establishment, brass...

jury_2

=> <u>body</u>

=> people

=> group, grouping

Figure 4: partial lattice for the sample sentence

In this example only hypo/hypernym links are shown. The concepts in WordNet are represented as lists of synonyms. Word senses to be disambiguated are shown in bold. Underlined concepts are those selected with highest Conceptual Density. Monosemic nouns have sense number 0.

2) Once the lattice is completed, the program starts the disambiguation loop until there are no words which remains to be disambiguated. For each loop the program computes the Conceptual Density of every concept in the lattice. For instance <administrative_unit> has underneath 3 senses to be disambiguated and a subhierarchy size of 96 producing a Conceptual Density of 0.256. Meanwhile, <body>, with 2 senses and subhierarchy size of 86, has a Conceptual Density of 0.062.

3) The concept with the highest Conceptual Density (<administrative_unit> in our example) is selected.

4) In this step two actions are performed. Firstly the program follows hyponym chains down from the concepts selected in step 3 (<administrative_unit>) and the senses of the words found in the bottom are selected as the correct senses (**operation_3**, **police_department_0** and **jury_1** are the senses chosen for <u>*operation*</u>, <u>*Police_Department*</u> and <u>*jury*</u>). All these nouns are considered to be disambiguated, even if more than one sense of a given word are below the concept selected in step 3. Lastly we build the lattice again as in step 1, but only considering the nouns not yet disambiguated. After that, the loop continues in step 2. In the example, the lattice is built for the senses of <u>*administration*</u> and <u>*prison_farms*</u>, but their senses yield non-overlapping lattices (for instance the lattice for **administration_1** would be the same as in figure 4 without **jury_2**), and therefore the loop terminates and we continue in step 5.

5) The program has three possible outcomes for the noun in the middle of the window; one sense has been selected (disambiguated), more than one sense has been selected (partially disambiguated, several senses of the noun are under the same selected concept) or the selection of a sense has been impossible due to the lack of information in the context.

After disambiguating the word in the current window the window moves forward, and the

police_department_0

=> local department, department of local government

=> government department

=> department

jury_1, panel

=> committee, commission

operation_3, function

=> division

=> administrative unit

=> unit

=> organization

=> social group

=> people

=> group, grouping

considering the other words in the window as context.

For each window, the program performs the next disambiguation algorithm:

```
(Step 1)tree := compute_tree(words_in_window)
       loop
(Step 2)tree := compute_conceptual_distance(tree)
(Step 3)concept := select_concept_with_highest_weigth(tree)
       if  concept = null then exitloop
(Step 4)tree := mark_disambiguated_senses(tree,concept)
       endloop
(Step 5)output_disambiguation_result(tree)
```

To illustrate the process, consider the following text extracted from SemCor:

The jury(2) praised the administration(3) and operation(8) of the Atlanta Police_Department(1), the Fulton_Tax_Commissioner_'s_Office, the Bellwood and Alpharetta prison_farms(1), Grady_Hospital and the Fulton_Health_Department.

Figure 3: sample sentence from SemCor

The underlined words are nouns represented in WordNet with the number of senses between brackets (those with a 1 are unambiguous nouns). SemCor links multiword terms using underscores. The noun to be disambiguated in our example is *operation*., and a window size of five will be used.

1) Given the set of nouns constrained by the context window size, our algorithm collects for every noun all its possible senses and hypernyms. All these concepts and connections are placed in a lattice. For each concept in the lattice, the program also stores the set of words that are generalised by the concept.

The following figure shows partially the lattice for the example sentence. Since *Prison_farm* appears in a different hierarchy we do not show it in figure 4:

5.*In fact the algorithm can disambiguate all the nouns in the window in one go, but we consider that the context is most informative for the noun in the center of the window. This and related issues are discussed in Section 6.*

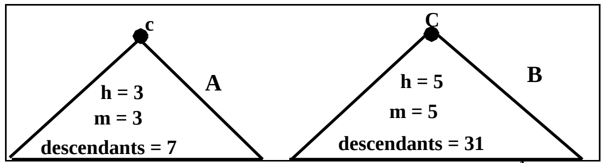

Figure 2: two hierarchies with CD = 1[4].

In order to tune the Conceptual Density formula, we have carried out several experiments adding two parameters, α and β. The α parameter modifies the strength of the exponential *i* because *h* ranges between 1 and 16 (the maximum number of levels in WordNet) while *m* ranges between 1 and the total number of senses in WordNet. Adding a constant β to *nhyp*, we tried to discover the role of the averaged number of hyponyms per concept. Formula 3 shows the resulting formula.

(3)

After a number of runs which were automatically evaluated, the results showed that β does not affect the behaviour of the formula, a strong indication that this formula is not sensitive to constant variations in the number of hyponyms. On the other hand, different values of α affected the performance consistently, yielding the best results in all the experiments where α was 0.20. The formula which was actually used in the experiments, thus, was the following:

(4)

where is the number of descendant senses of the concept *c*.

We have tested the formula in two different ways (see Section 5). The first one involves the manner in which *nhyp* and are calculated. The second arises from the manner in which the hierarchy is constructed: considering only hypo/hypernymy links, or including meronymic links as well.

4 The Disambiguation Algorithm Using Conceptual Density

The algorithm to disambiguate a given noun w in the middle of a window of nouns W roughly proceeds as follows. First, the algorithm represents in a lattice the nouns in the window, its senses and hypernyms (step 1). Then, the program computes the Conceptual Density of each concept in WordNet according to the senses it contains in its subhierarchy (step 2). It selects the concept c with the highest density (step 3) and select the senses below it as the correct senses for the respective words. If a word from W (step 4):

- has a single sense under c, it has already been disambiguated.
- has no a sense, it is still ambiguous
- has more than one sense with highest density, we can eliminate all the other senses of w, but have not yet completely disambiguated w.

It proceeds then to choose the next concept with highest density, and continues to disambiguate words in W. In the end the senses left for w are analysed and the result is output (step 5). This process will be further explained below.

Given a window size, the program moves the window one word at a time from the beginning of the document towards its end, disambiguating the word in the middle of the window[5] and

---

4.From formulas 1 and 2 we have:

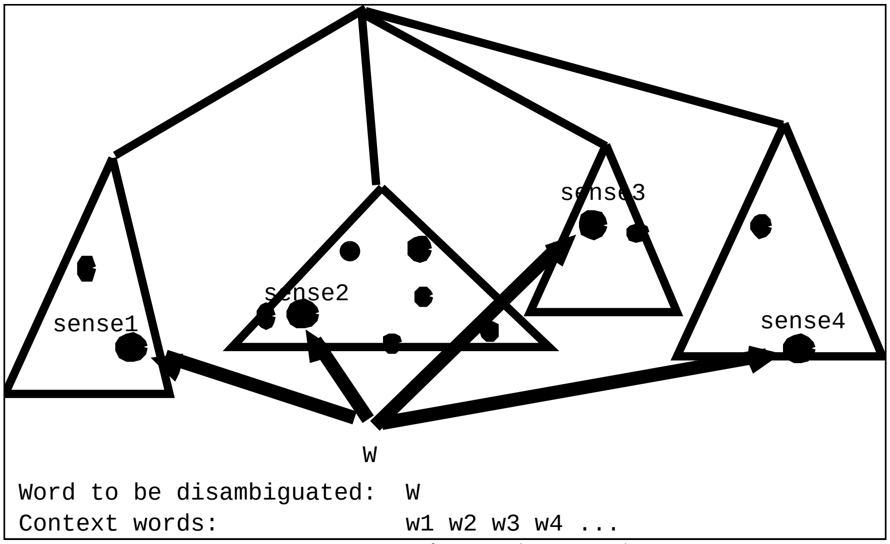

Figure 1: senses of a word in WordNet

The sense of W contained in the subhierarchy with highest Conceptual Density will be chosen as the sense disambiguating W in the given context. In figure 1, sense2 would be chosen.

Given a concept *c*, at the top of a subhierarchy, and given *nhyp* and *h* (mean number of hyponyms per node and height of the subhierarchy, respectively), the Conceptual Density for *c* when its subhierarchy contains a number *m* (marks) of senses of the words to disambiguate is given by the formula below:

(1)

The numerator expresses the expected area for a subhierarchy containing *m* marks (senses of the words to be disambiguated), while the divisor is the actual area, that is, the formula gives the ratio between weighted marks below *c* and the total area of the subhierarchy below *c*. The weight given to the marks tries to express that the height and the number of marks should be proportional.

nhyp is computed for each concept in WordNet in such a way as to satisfy equation 2, which expresses the relation among height, averaged number of hyponyms of each sense and total number of senses in a subhierarchy if it were homogeneous and regular:

(2)

Thus, if we had a concept *c* with a subhierarchy of height 5 and 31 descendants, equation 2 will hold that *nhyp* is 2 for *c*.

Conceptual Density weights the number of senses of the words to be disambiguated so as to make density equal to 1 when the number *m of* senses below *c* is equal to the height of the hierarchy *h*, to make density smaller than 1 if *m* is smaller than *h* and to make density larger than 1 whenever *m* is larger than *h*. The density can be kept constant for different *m*-s provided a certain proportion between the number of marks *m* and the height *h* of the subhierarchy is maintained. Both hierarchies **A** and **B** in figure 2, for instance, have Conceptual Density 1. For the sake of clarity we have assumed uniform hierarchies.

3 Conceptual Density and Word Sense Disambiguation

A measure of the relatedness among concepts can be a valuable predictive knowledge source for several decisions in Natural Language Processing. For example, the relatedness of a certain word-sense to the context allows us to select that sense over the others, and actually disambiguate the word. Relatedness can be measured by a fine-grained conceptual distance [Miller & Teibel 91] among concepts in a hierarchical semantic net such as WordNet. This measure would allow the discovery of the most lexically cohesive set of senses of a given set of words in English.

Several measures of relatedness among words based on cooccurrence in a text have been described; mutual information, t-test, etc. [Church et al. 91], the cosine function in Context Space [Schütze 92], conditional probability [Wilks et al. 93]. [Resnik 93] combines a knowledge based approach involving semantic classes taken from WordNet with cooccurrence data extracted from corpora. Less attention has been paid lately to measures of relatedness based on semantic structured hierarchical nets.

Conceptual distance tries to provide a basis for determining closeness in meaning among words, taking as reference a structured hierarchical net. The conceptual distance between two concepts is defined in [Rada et al. 89] as the length of the shortest path that connects the concepts in a hierarchical semantic net. Besides applying conceptual distance in a medical bibliographic retrieval system and merging several semantic nets, they demonstrate that their measure of conceptual distance is a metric. In a similar approach, [Sussna 93] employs the notion of conceptual distance between network nodes in order to improve precision during document indexing. Following these ideas, [Agirre et al. 94] describes a new conceptual distance formula for automatic spelling correction and [Rigau 94], using this conceptual distance formula, presents a methodology to enrich dictionary senses with semantic tags extracted from WordNet.

The measure of conceptual distance among concepts we are looking for should be sensitive to:

- the length of the shortest path that connects the concepts involved.
- the depth in the hierarchy: concepts in a deeper part of the hierarchy relatively closer than those in a more shallow part.
- the density of concepts in the hierarchy: concepts in a dense part of the hierarchy are relatively closer than those in a more sparse region.

But also:

- the measure should be independent of the number of concepts we are measuring.

We have experimented with several formulas that follow the four criteria presented above. Currently, we are working with a variant of conceptual distance which we call Conceptual Density that compares areas of subhierarchies.

As an example of how Conceptual Density can help to disambiguate a word, in figure 1 the word W has four senses and several context words. Each sense of the words belongs to a subhierachy of WordNet. The dots in the subhierarchies represent the senses of either the word to be disambiguated (W) or the words in the context. Conceptual Density will yield the highest density for the subhierarchy containing more senses of those, relative to the total amount of senses in the subhierarchy.

mantic Concordance or Semcor for short. We also use a public domain lexical knowledge resource, WordNet [Miller 90]. The advantage of this approach is clear; Semcor provides an appropriate environment for testing our procedures in a fully automatic way.

This paper presents a general automatic decision procedure for lexical ambiguity resolution based on a formula of conceptual distance among concepts: Conceptual Density. The procedure needs to know how words are clustered in semantic classes and how semantic classes are hierarchically organised. For this purpose, we have used a broad semantic taxonomy for English, WordNet. We have performed several experiments employing the notion of Conceptual Density among concepts in a structured hierarchical net. Given a piece of text from the Brown Corpus, our system tries to resolve the lexical ambiguity of nouns finding the combination of senses from a set of nouns in context that maximises the total Conceptual Density among senses.

In order to test our algorithms, we have selected at random four texts of SemCor. Our procedure only considers the words in SemCor with a noun part of speech tag. We discarded the nouns not present in WordNet (averaging around 10% of the nouns in all four texts)

Improvement in disambiguation compared with chance is clear and consistent, strongly suggesting that knowledge-based algorithms are competitive with statistically-based approaches, with the advantage of not needing training.

Even if this technique is presented as stand-alone, it is our belief, following the ideas of [McRoy 92] that full-fledged lexical ambiguity resolution should combine several information sources. Conceptual Density might be only one of a number of complementary sources of evidence for evaluating the plausibility of a certain word sense.

In section 2 we present the semantic knowledge sources used by the system. In section 3, we define Conceptual Density. In section 4, we discuss the disambiguation algorithm used in the experiment and in section 5, we explain and evaluate the experiments performed. In section 6, we discuss future directions and, finally, in the last section, we draw some conclusions.

2 WordNet and the Semantic Concordance

Sense is not a well defined concept and often has subtle distinctions in topic, register, dialect, collocation, part of speech, etc. For the purpose of this study, we take as the senses of a word those senses provided by WordNet 1.4 [Miller 90].

WordNet is an on-line lexicon based on psycholinguistic theories. It comprises nouns, verbs, adjectives and adverbs, organised around semantic relations, such as: synonymy and antonymy, hypernymy and hyponymy, meronymy and holonymy. Lexicalised concepts, represented as sets of synonyms called synsets, are the basic elements of WordNet. The senses of a word are represented by synsets, one for each word sense. The version used in this work, WordNet 1.4, contains 83,800 words, 63,300 synsets (word senses) and 87,600 links between concepts.

The nouns of WordNet can be viewed as a tangled hierarchy of hypo/hypernymy relations. Nominal relations include also three kinds of meronymic relations, which can be paraphrased as "member-of", "made-of" and "component-part-of".

SemCor [Miller et al. 93] is a corpus where part of speech and word sense tags (which correspond to WordNet synsets) have been included for all open-class words. SemCor is a subset taken from the Brown Corpus [Francis and Kucera, 67] which comprises approximately 250,000 words from a total of 1 million words. The coverage in WordNet of the senses for open-class words in SemCor reaches 96% according to Miller et al. The tagging was done manually, and the error rate reported is around 10% for polysemous words.

An Experiment on Word Sense Disambiguation of the Brown Corpus using WordNet[1]

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Abstract.

This paper presents a method for the resolution of lexical ambiguity and its automatic evaluation over the Brown Corpus. The method relies on the use of the wide-coverage noun taxonomy of WordNet and the notion of conceptual distance among concepts, captured by a Conceptual Density formula developed for this purpose. This fully automatic method requires no hand coding of lexical entries, hand tagging of text or any kind of training process. The results of the experiments have been automatically evaluated against SemCor, the sense-tagged version of the Brown Corpus.

Keywords: Word Sense Disambiguation, Conceptual Distance, WordNet, SemCor.

1 Introduction

Word sense disambiguation is a long-standing problem in computational linguistics. Much of recent work in lexical ambiguity resolution offers the prospect that a disambiguation system might be able to input unrestricted text and tag each word with the most likely sense with fairly reasonable accuracy and efficiency. The main idea is to attempt to use the context of the word to be disambiguated together with information about each of its word senses to solve this problem.

Several interesting experiments have been performed in recent years using pre-existing lexical knowledge resources. [Cowie et al. 92] and [Guthrie et al. 93] describe a method for lexical disambiguation of text using the definitions in the machine-readable version of the LDOCE dictionary as in the method described in [Lesk 86], but using simulated annealing for efficiency reasons. [Yarowsky 92] combines the use of the Grolier encyclopaedia as a training corpus with the categories of the Roget's International Thesaurus to create a statistical model for the word sense disambiguation problem with excellent results. [Gale et al. 93] explains a statistical approach using bilingual parallel corpora. [Wilks et al. 93] perform several interesting statistical disambiguation experiments using cooccurrence data collected from LDOCE. [Sussna 93], [Voorhees 93] and [Richarson et al. 94] define disambiguation programs based in WordNet with the goal of improving precision and coverage during document indexing.

Although each of these techniques looks somewhat promising for disambiguation, either they have been only applied to a small number of words, a few sentences or they are not in a public domain corpus. For this reason we have tried to disambiguate all the nouns from texts in the sense tagged version of the Brown corpora [Francis & Kucera 67], [Miller et al. 93], also called Se-

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Conceptual Distance And Automatic Spelling Correction

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ABSTRACT. Text from different sources usually arrives under imperfect conditions. When an anomalous word is detected automatic word recognisers produce a list of candidates from which only one is correct. A variety of techniques have been devised to discriminate among the possible correction candidates. The project we are involved in tries to exploit linguistic knowledge in Spelling Correction. A preliminary investigation shows syntactic discrimination not to be enough. The gap could be covered by semantic techniques like conceptual distance. Basically, we define conceptual distance between two concepts as the shortest path length in the hierarchies of the lexical knowledge base of IDHS (Intelligent Dictionary Help System). We consider that a correction proposal that is closer to the surrounding words in the sentence is more plausible enabling us to produce a ranking of the proposals. It is our belief that conceptual distance can be also applied to other word recognition areas, such as handwriting recognition or optical character recognition, where a single proposal would also be desirable.

1 Introduction

Text from different sources usually arrives under imperfect conditions. The medium of transmission conditions the type of automatic word recognition to be used: Optical Character Recognition, Speech Processing or Spelling Correction. When an anomalous input is encountered these recognisers produce a list of candidates from which only one is correct. There are a number of applications e.g. Text-to-Speech Synthesis, that in order to rule out human intervention need automatic correction, that is, the first choice of the correct proposal among the correction candidates.

The task of choosing the appropriate correction proposal is not an easy one. We have to draw knowledge from several sources, as one technique alone would not suffice. In this direction [Kukich, 92] points out, for spelling correction and considering isolated words only, that automatic correction performed by humans scored from %65 to %82. These figures could represent an upper bound for automatic techniques that do not take context into account. To leave %35-%18 of the detected errors uncorrected would be unsatisfactory for the applications mentioned earlier. In order to increase the performance and get an acceptable correction rate, some sort of context modelling, linguistic or other, would be needed.

The project we are involved in tries to exploit linguistic knowledge for automatic spelling correction. This paper focuses on the contribution of lexical-semantic techniques in general, and conceptual distance in particular. Some other work is being carried on the syntactic side.

The idea of conceptual distance captures the intuition that some words are more related or closer than others. We consider that a correction proposal that is closer to the surrounding words in the sentence is more plausible. Thus we can produce a ranking of the proposals.

Basically, we define conceptual distance between two word senses as the shortest path length in the hierarchies of the Dictionary Knowledge Base of IDHS (Intelligent Dictionary Help System [Artola, 93; Agirre et al., 94]), following the ideas of [Rada et al., 87]. The knowledge base of IDHS is a semantic network of frames where each frame represents a word sense from a dictionary. Arcs between frames represent lexical-semantic relations derived from the definitions in a machine readable dictionary.

Next section shows some experimental results that indicate the need of more linguistic knowledge beyond syntax in spelling error correction, followed by an overview of IDHS. After that, two prospective semantic techniques are introduced, from which conceptual distance is explored in depth in the next section. Finally some conclusions are presented.

Originally, the target language was Basque, but later developments in IDHS made us switch to French. For this reason the preliminary collection of data was done for Basque, while the implementation is being run on French texts. The examples in sections 2 and 4 are in Basque, while those in section 5 are in French.

2 ON THE NEED OF SEMANTIC DISCRIMINATION

In order to have some hard data on the convenience and prospective performance of the semantic contribution to automatic error correction, the analysis of a small corpus was performed. The error detection and the list of proposals have been taken from the spelling checker/corrector XUXEN [Aduriz et al, 1993; Agirre et al., 1992]. The texts come from 48 Basque language learners, giving a total of 8290 words. XUXEN generated proposals for 305 spelling errors, producing multiple proposals 182 times (60%).

The syntactic analysis of the texts, as well as the syntactic discrimination of the proposals, was performed by a person simulating an automatic full-fledged and robust parser. The proposals which would lead to grammatical errors where thus removed from the proposal lists. The semantic discrimination was applied only after the syntactic phase was completed.

The results hold that syntax alone could select one single proposal 70% of the cases. This result might be too optimistic, considering that the syntactic analyser was supposed to be complete and robust.

The semantic information faced the cases where syntax could not do the job. Applying by hand the semantic techniques explained below, it managed to solve 63% of the misspellings. It might be that this experiment favoured syntax, leaving semantics the tough cases. Anyway, the performance of both is similar, and the experiment indicates that their combination is desirable in order to get better results, up to 90% in this particular experiment. These results are tentative, awaiting confirmation of implemented systems with realistic syntactic and semantic coverage.

XUXEN: 305 errors with proposals		
1 prop.	123	40.3%
n prop.	182	59.7%
syntactic discrimination on 182 errors		
success	128	70.3%
fail	54	29.7%
semantic discrimination on 54 errors		
success	34	62.9%
2/3	11	20.3%
fail	9	16.8%

3 IDHS

IDHS (Intelligent Dictionary Help System) provides the base for semantic correction. It provides both a representation language suited to explore the techniques presented in the following section, and also the semantic knowledge itself.

IDHS was conceived as a monolingual (explanatory) dictionary system for human use [Artola & Evrard, 92; Artola, 93]. The system provides various access possibilities to the data, allowing to deduce implicit knowledge from the explicit dictionary information. The system has been implemented on a symbolic architecture machine using KEE knowledge engineering environment.

The starting point of IDHS is a Dictionary Database (DDB) built from an ordinary French dictionary. Meaning definitions have been analysed using linguistic information from the DDB itself and interpreted to be structured as a Dictionary Knowledge Base (DKB). As a result of the parsing different lexical-semantic relations between word senses are established by means of semantic rules (attached to the patterns); rules are used for the initial construction of the DKB.

The interconceptual lexical-semantic relations detected from the analysis of the source dictionary are classified into paradigmatic and syntagmatic. Among the paradigmatic relations, the following have been found: synonymy and antonymy, taxonomic relations as hypernymy/ hyponymy —obtained from definitions of type "genus et differentia"— and taxonymy itself (expressed by means of specific relators such as sort-of and kind-of), meronymy, and others. Whereas among the syntagmatic relations we can find case relations (e.g. agent, object, goal, etc.), relations derived from the specific lexicographic metalanguage (e.g. quality-of, act-of, property), and others.

The knowledge representation scheme chosen for the DKB of IDHS is composed of three elements, each of them structured as a different knowledge base. One of this components, KB-THESAURUS, implements the dictionary as a semantic network of frames, where each frame represents a one-word concept (word sense) or a phrasal concept. Phrasal concepts represent phrase structures associated to the occurrence of concepts in meaning definitions. Frames are interrelated by slots representing lexical-semantic relations. Other slots contain phrasal, meta-linguistic, and general information.

In the following section we tackle spelling correction from the point of view of semantics and IDHS.

4 SEMANTIC DISCRIMINATION

As we already mentioned, this work focuses primarily on the contribution of semantics, and more precisely in the use of lexical-semantic information. We have considered the use of the following:

Selectional Restrictions

Selectional restrictions indicate semantic constraints that the arguments of verbs, adjectives or nouns have to fulfil. For example:

```
jan      => verb[agent: animate,
                 object: edible]
ilegorri => adj.[argument: person]
anaia    => noun[argument: person]
```

These can be read as 'the verb `jan` (eat) takes as agent an animate entity and as object and edible entity', 'the argument of `ilegorri` (blonde) has to be a person', etc.

The contribution of selectional restrictions will be illustrated by the following example from the Basque corpus. Had someone typed `lehio` in Basque we would get the proposals below[1]:

```
lehio: lehia, lesio, leiho
```

If the misspelling occurs in the following sentence, and assuming a sample selectional restriction for `apurtu` (to break),

```
"lehio bat apurtu dut"²
apurtu =>  [agent: animal,
            object: physical-object]
```

we would be able to discard competition and injury, and select the only proposal that fulfils the restriction of being a physical object, `leiho` (window).

Conceptual Distance

The idea of conceptual distance tries to capture the intuition that some words are closer or more related than others. Therefore we can consider devising a metric that would give results similar to the following[3]:

```
dist(itsasontzi,kapitain) = "short"
dist(itsasontzi,teklatu) = "long"
```

The idea is that we prefer proposals that are related or conceptually close to the other words in the sentence, rather than unrelated or distant proposals. This approach has multiple variants, depending on whether we take all the words in the sentence, or we only take the measurements with some relevant words in the sentence.

Let us consider the following example[4]:

```
uzaina: zaina, usaina, uhaina
"ukenduaren uzainak erlea aldendu zuen"
```

We can compare the distance of the proposals with the other words in the

---

1 The proposals mean respectively competition, injury, window.

2 Meaning *I broke a <lehio>*. All the basque examples and proposals in the paper are taken from a small corpus and the correction proposals are all from Xuxen

3 The words mean respectively *ship, captain, keyboard.*

4 The proposals mean, respectively, *vein, smell, wave.* The sentence means *the <uzaina> of the ointment kept away the bee.*

sentence. The result would be that `usaina` (smell) holds the minimum total distance, and therefore would be preferred as the correct proposal. This technique will be further explained below.

5 CONCEPTUAL DISTANCE AND SPELLING CORRECTION

Mainstream approaches to conceptual distance rely on structured inheritance nets or similar kinds of knowledge bases. For instance, [Rada et al., 89] defines conceptual distance in terms of the length of the shortest path of IS-A links between the word senses of the Mesh semantic net. Besides applying distance in a medical bibliographic retrieval system, they also try to use it as a tool for merging semantic nets.

In a similar approach, [Sussna, 93] assigns a weight to each link in the Wordnet semantic network and calculates the distance between two word senses as the total weight of the path with minimum weight. The weights try to capture additional data, e.g. tfor the same path length, word senses lower in the hierarchy seem to be conceptually closer.

These two approaches take into consideration that words have multiple senses. In fact [Sussna, 93] devises his measure with the purpose of sense-disambiguating a text for indexing and text retrieval.

The knowledge representation of IDHS provides support for the experimentation of several distance measures, allowing us to select the most suitable for proposal discrimination. Previous works on conceptual distance rely mainly on hierarchical relations (hypernymy, taxonymy, meronymy), but distance measures could also profit from the other semantic relations in IDHS. [Rada et al., 89] point out that the proliferation of semantic relations makes distance unreliable. Such systems (e.g. [Collins et Loftus, 75]) have to provide a complex weighting mechanism to balance the heterogeneous nature of the relations. In order to avoid that, it would be desirable to use certain semantic relation only when appropriate, that is, when it makes sense in the given context. This idea will be developed below, while considering the issues related to the application of conceptual distance to correction.

Path-Finding Algorithms

In the heart of the distance algorithm there is a path-finding algorithm. Given two word senses in IDHS, the algorithm would find the shortest path(s) of lexical-semantic links between both. In order to be able to test different correction strategies the following algorithms have been implemented:

`h-path(n1,n2)`: finds the path following hierarchical links only: hypernym, part-of, component-of, element-of, sort-of and their respective inverse relations.

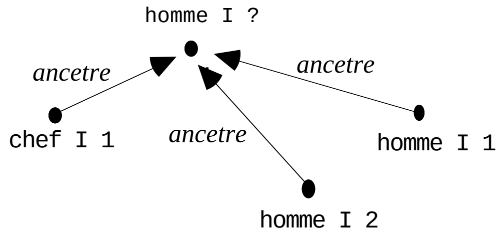
`s-path(n1,n2,r1,...,rn)`: finds a path that has to contain at least one non-hierarchical (semantic) link from the set {r1,...,rn}, alongside the previously mentioned hierarchical links.

`s*-path(n1,n2)`: finds a path that may contain any non-hierarchical (semantic) relation, alongside the hierarchical links.

The first algorithm, `h-path`, constraints the search to hierarchical relations only. It is considered the most reliable for conceptual distance, but it imposes several limitations. The two word senses need to be in the same hierarchy, which implies that `h-path` will never find a path across different parts of speech. For the same reason, it needs very comprehensive hierarchies, which are difficult to create or acquire. Other semantic relations could alleviate this, relating concepts across hierarchies.

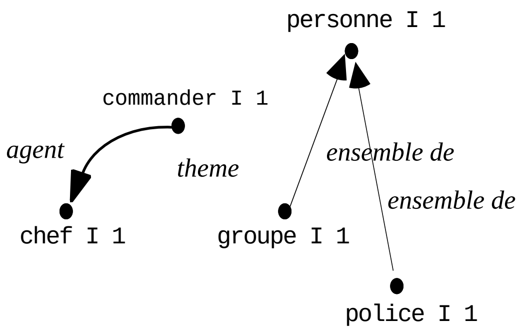
The use of unconstrained semantic relations as in `s*-path`, though, can produce nonsense paths that have to be neutralised when calculating the actual distance figures. It also has heavy efficiency burdens, which can be reduced constraining the set of acceptable relations. If the set of relations is constrained according to semantic criteria, the paths will be semantically coherent. The set of acceptable relations for a certain pair of word senses could be deduced from context, or in some cases, from the part of speech of the word senses. For instance, IDHS admits two relations for a noun that have an adjective as value: property and quality-of. In that case `s-path` will return a path that relates both noun and adjective via property, quality-of and the hierarchical relations.

Some examples of the algorithms follow:



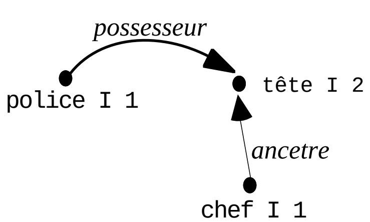
h-path(chefI1, hommeI1) =
chefI1 *ancetre* hommeI? *descendant* hommeI1

The path found by `h-path` between the first word sense of *boss* and the first sense of *man* means: *bossI1 is an ancestor*[5] *of manI?* (a non-disambiguated sense that includes all other senses of man), *which has as descendant manI1*.



s*-path(chefI1, policeI1) =
chefI1 *agent+inv* commanderI1 *theme* groupeI1 *ensemble de* personneI1 *element de* policeI1

The path found by `s*-path` between the first word sense of *boss* and the first sense of *police* means: *bossI1 is an agent of to-commandI1 which has as object groupI1, which is a set-of personI1 which is an element-of policeI1*.



s-path(chefI1,policeI1,possesseur+inv) =
chefI1 *ancetre* têteI2 *poss.+inv* policeI1

The path found by `s*-path` between the first word sense of *boss* and the first sense of *police* means: *bossI1 is a descendant of headI2 (as in head of department), which is "owned" by policeI1*.

The general search of a path between two nodes has exponential complexity, in the order of $O(c^n)$, where `c` is the average of the number of links per word sense, and `n` is the length of the path. In order to keep it under control, the length of the path has to be limited beforehand. This limit can be interpreted as the point after which we consider the two nodes to be unrelated or "very" far. Accordingly, this limit should be "tuned" having in consideration both efficiency and conceptual suitability.

The complexity of the three algorithms grows from the first to the last. While `h-path` deals with five hierarchical relations ($c \leq 5$) and `s-path` is devised to also take into account a small set of relations of the same kind (one to four extra relations, $c \leq 9$), `s*-path` has to provide for the whole set of relations (ranging from 10 to 40 depending on the part of speech of the word sense).

Conceptual Distance

The path(s) between two word senses is(are) the base for conceptual distance. But other facts have to be also considered. The empirical results of [Sussna, 93] show that, as already mentioned at the beginning of this section, the length of the path and the specificity of the word senses in the path (measured by the depth in the hierarchy) are the important parameters that affect the distance measure he proposes. The second parameter tries to capture the fact that specific word senses are considered closer than more general ones.

Our conceptual distance reflects those parameters in the following formula:

$$\mathbf{distance}(ws_1, ws_n) = \sum_{i=1}^{n} \mathbf{1}/\mathbf{depth}(ws_i)$$

where $< ws_1 \ldots ws_i \ldots ws_n >$ is the path from ws_1 to ws_n, and $\mathbf{depth}(ws_i)$ is the depth of ws_i in the taxonomy.

Other parameters that could help tuning the measure have not been considered yet. One parameter, for example, could involve giving different weights to each relation, in a way similar to the "criteriality tags" used by [Quillian, 68]. The inclusion of these parameters in the above formula depends greatly on empirical results, which have not yet been gathered.

Correction

As mentioned in section 4, we perform correction choosing the proposal that is more

---

5 Ancestor includes the concepts in the transitive closure of hypernymy. Descendant includes the concepts in the transitive closure of hyponymy.

related or conceptually closer to the other words in the sentence, and leaving aside unrelated or distant proposals. The relatedness of a given proposal with the surrounding sentence can be measured using a variety of strategies.

g-correction (generalised). Distance as defined above is measured between word senses. Consequently all the senses in the dictionary for the words in the sentence and the proposals have to be considered. This means that inappropriate senses could bias the corrector to choose an incorrect proposal. In order to rule out, or at least try to neutralise, these spurious readings, and at the same time choose the correct proposal, the following technique can be used: the preferred senses and proposals will be the ones that give minimal pairwise conceptual distance.

Thus, if we have a sentence of length N $<w_1, w_2, ...w_n>$ with M spelling errors $\{e_1=w_i...e_m=w_j\}$, and a list of proposals for each error $P(e_i) = <p_{i1},...p_{iL}>$, we need to consider the senses of all non-error words and the proposals. For each possible combination of senses (mixing both non-error words and proposals), the winning combination will be the one with the minimal total of pairwise distances. This winning combination will give both the preferred proposals and word senses.

In figure 1, it can easily be seen that for long sentences with highly ambiguous words and many correction proposals, the number of combinations and pairwise distance computations grows enormously.

c-correction (constrained). If we want to limit both the number of combinations and the pairwise distance computations, we can focus on doing proposal discrimination only. We are not trying to sense-disambiguate now, and will thus consider of equal value incorrect word senses and appropriate ones.

For each proposal we will only compute the distances of its corresponding word senses with each word sense of the non-error words in the sentence (cf. fig. 2). The proposal that gets the minimum total distance wins.

```
Sentence:   le cheé de la police reunit vingt hommes sur la place du village.
Error:  cheé                       Proposals:   chef cher chez chié chieé chéri chic

Word Senses in IDHS:
   Sentence:  police I 1, police I 2,
              reunir I 1, reunir I 2, reunir I 3, reunir I 4, reunir I 5
              homme I 1, homme I 2, homme I 3, homme I 4, homme I ?
              place I 1, place I 2, place I 3, place I 4, place I 5, place I ?
              village I 1
   Proposals: chef I 1, cher I 1, cher I 2, chéri I 1, chic I 1

Combinations:
   C1)        police I 1, reunir I 1, homme I 1, place I 1, village I 1, chef I 1
   C2)        police I 2, reunir I 1, homme I 1, place I 1, village I 1, chef I 1
       ...
      Number of combinations:  2x5x5x6x1x5 = 1.500

Distance on C1:
      dist(police I 1, reunir I 1) ... dist(police I 1, chef I 1)     n=5
      dist(reunir I 1, place I 1)  ... dist(reunir I 1, chef I 1)     n=4
      ...
      dist(village I 1, chef I 1)                                      n=1

      Number of distance calls:
              [total]   1500 x (5+4+3+2+1) = 1500 x 15 = 22.500
              [distinct pairs]                            239
```

fig. 1. Combinations in **g-correction**.[6]

---

[6] The sentence means "the *cheé* of the police gathered twenty men in the square of the village". The proposals for cheé are: boss, expensive, ´home of´, dear and stylishness..

```
Combinations:
   chef I 1  police I 1, police I 2,
             reunir I 1, reunir I 2, reunir I 3, reunir I 4, reunir I 5
             homme I 1, homme I 2, homme I 3, homme I 4, homme I ?
             place I 1, place I 2, place I 3, place I 4, place I 5, place I ?
             village I 1
   ...
   chic I 1  police I 1, police I 2,
             reunir I 1, reunir I 2, reunir I 3, reunir I 4, reunir I 5
             homme I 1, homme I 2, homme I 3, homme I 4, homme I ?
             place I 1, place I 2, place I 3, place I 4, place I 5, place I ?
             village I 1

      Number of combinations: 5

Distance:
   C1)       dist(chef I 1, police I 1) ... dist(chef I 1, village I 1)
             ...
             dist(chic I 1, police I 1) ... dist(chic I 1, village I 1)

      Number of distance calls:
        [total]    5x(2+5+5+6+1)= 95
```

fig. 2. Combinations in **c-correction**.

Although the wrong word sense may contribute to credit incorrect proposals, the greater number of related true senses will add up and eventually the correct proposals will be chosen.

s-correction (*"semantic"*). We have already introduced two path-finding algorithms (`s-path` and `s*-path`) that traverse non-hierarchical semantic relations. The semantic clues in the sentence can be used to inform `s-path` about the relations that can be expected in the path between the two word senses. Figure 3 illustrates a simplified example of the semantic relations in the sentence from figure 1. The preposition *de* can be interpreted as meaning owner, location etc. For the example below, calling `s-path` with the corresponding word senses will find a path. We already saw an example when examining path-finding.

```
Semantic relations:

   from the verb:
   (reunit agent cheé)
   ...
   from the preposition de:
   (cheé possesseur+inv police)
   (cheé location police)
   ...
Combinations & Distance:
   reunir I 1 chef I 1...chic I 1
   ...
   reunir I 5 chef I 1...chic I 1

   chef I 1...chic I 1 police I 1
   chef I 1...chic I 1 police I 2

   ...

   Number of combinations:  5+2+2=9
   Number of dist. calls:     9x5=45
```

fig. 3. Combinations in **s-correction**.

This kind of semantic interpretation does not require as heavy a linguistic machinery as it might seem. Triples like those of the example are readily obtained by semantic information extraction systems from corpora [Velardi et al., 91].

6 Conclusions And Further Work

We have outlined the application of a specific semantic technique, conceptual distance, in automatic spelling correction.

In previous implementations of conceptual distance, only `h-path` style algorithms have been used. These algorithms need comprehensive hierarchies, which are difficult to construct. Other semantic relations. i.e. non-hierarchical relations, can serve to relate word senses even if they do not share the same hierarchy, and specially in the case of two word senses from different grammatical categories. These extra semantic relations could be exploited by conceptual distance using `s*-path` and `s-path`. Selectional restrictions are also an alternative in this kind of situations.

`s*-path` has coherence and efficiency problems which are alleviated in `s-path`. But in order to use `s-path` properly, semantic information from the context of the error has to be obtained. This semantic analysis and the tuning of the specific relations needed in a certain context are the work we are focusing on now.

In a further step, we are also planning to develop a more efficient application-oriented representation of the semantic knowledge. For that purpose, we will try to identify and map the relevant subset of the representation of IDHS.

Other important issue is the application of the different correction strategies to real data, where their performance should be effectively contrasted. In this sense, IDHS, because of the rich variety of semantic relations extracted from the dictionary, is very well suited as a platform for extensive testing of the issues above.

It is our believe that the correction techniques explored in this paper, although originally designed for spelling correction, are not dependent of the error source. As long as they are applied on linguistic input they could be used in other word recognition areas where automatic correction, i.e. single correction proposals, would be desirable.

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Lexical-semantic information and automatic correction of spelling errors.

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1. INTRODUCTION.

This study focuses on the use of lexical-semantic information for the automatic discrimination of the proposals generated by a spelling corrector. Current spelling checkers only detect non-word errors, e.g. *sgip*, *shap* instead of *ship*, but would not notice *sip* as a misspelling of *ship*. Moreover, they hand out a list of correction proposals, leaving to the user the decision of which one was the intended word, for instance[1]:

```
araso*:   eraso, arazo, arasa, arbaso
```

In general, it is not possible to guess which one is the correct proposal in isolation, we need to examine the context2:

"araso hau konpontzeko eskatu dut."

Confronted with this sentence, a Basque speaker would choose 'arazo' (*problem*) as the correct word. A system able to take this decision should include at least syntactic and also semantic information. In the example above, for instance, syntax can not eliminate any proposal, being all from the same syntactic category. Semantic information, on the contrary, strongly indicates that what you *solve* has to be an 'arazo' (*problem*), rejecting the other proposals.

This paper presents firstly an overview of some prospective techniques. In the third section the results of a study in a small corpus are also commented. Next, the way in which IDHS, Intelligent Dictionary Help System [Arregi et al., 1993], can be applied is explored. Finally some conclusions and proposals for future work are suggested

---

1 For the misspelled araso, the spelling corrector for Basque Xuxen gives a list of proposals which mean respectively *attack*, *problem*, *shelf* and *ancestor*. All the examples and proposals in the paper are taken from a small corpus and the correction proposals from Xuxen [Aduriz et al., 1993] [Agirre et al., 1992].

2 The sentence means: *I asked to solve this <araso>*.

2. LEXICAL SEMANTIC TECHNIQUES.

As we already mentioned, this work focuses primarily on the contribution of semantics, and more precisely in the use of lexical-semantic information. We are considering the use of the following:

1) selectional restrictions

Selectional restrictions indicate semantic constraints that the arguments of verbs, adjectives or nouns have to fulfil. For example:

```
eat      => [agent: animate, object: edible]
blonde   => [argument: person]
brother  => [argument: person]
```

These can be read as 'the verb *eat* takes as agent an animate entity and as object and edible entity', 'the argument of *blonde* has to be a person', etc.

The contribution of selectional restrictions will be illustrated by the following example. Had someone typed `lehio` in Basque we would get the proposals below[3]:

```
lehio:    lehia, lesio, leiho
```

If the misspelling occurs in the following sentence, and assuming a sample selectional restriction for `apurtu` (*to break*),

```
"lehio bat apurtu dut"
```
[4]

```
apurtu =>   [agent:animal,
             object: physical-object]
```

we would be able to discard competition and injury, and select the only proposal that fulfils the restriction of being a physical object, `leiho` (*window*).

2) lexical-conceptual distance

The idea of lexical-conceptual distance tries to capture the intuition that some words are closer or more related than others. Therefore we can consider devising a metric that would give results similar to the following:

---

[3] The proposals mean respectively *competition, injury, window.*

[4] Meaning *I broke a <lehio>.*

```
distance(ship, captain) = "short"
distance(ship, keyboard) = "long"
```

The idea is that we prefer proposals that are related or conceptually close to the other words in the sentence, rather than unrelated or distant proposals. In order to only take the measurements with the relevant words in the sentence, it would be desirable that a syntactic analysis had been performed.

Let us consider the following example:[5]

```
uzaina:   zaina, usaina, uhaina
"ukenduaren uzainak erlea aldendu zuen"
```

We choose to compare the distance of the proposals (which are the subjects of the sentence) with their complement `ukendu` (ointment) and the direct object `erle` (bee). The result would be that `usaina` (*smell*) holds the minimum total distance, and therefore would be preferred as the correct proposal.

```
total = dist(ukendu,X) + dist(erle,X)
```

3 ANALYSIS OF THE ERRORS IN A SMALL CORPUS OF BASQUE

In order to have some hard data on the convenience and prospective performance of the semantic contribution to automatic error correction, the analysis of a small corpus was performed. The error detection and the list of proposals have been taken from the spelling checker/corrector XUXEN. The texts come from Basque language learners, giving a total of 8000 words. From the nearly 500 spelling errors XUXEN detected, 182 errors involved multiple proposals.

The syntactic analysis, as well as the syntactic discrimination of the proposals was performed by a person simulating an automatic parser. The semantic discrimination was applied only to the proposals deemed correct by the syntactic phase.

The results hold that syntax alone could select one single proposal 70% of the cases. This result might be too optimistic, considering that the syntactic analyzer was supposed to be complete and robust. The semantic information was faced with the cases where syntax could not do the job, and managed to solve 63% of the misspellings. The performance of both is similar, and the

[5] The proposals mean, respectively, *vein, smell, wave*. The sentence means *the <uzaina> of the ointment kept away the bee.*

experiment indicate that their combination is desirable in order to get better results, up to 90% in this particular experiment.

4 IDHS AND THE ACQUISITION OF THE REQUIRED LEXICAL-SEMANTIC INFORMATION

One of the motivations of this work is to take profit from the relations and deductive power available in IDHS, which is constructed from conventional dictionaries. Each kind of semantic information is studied in turn:

1) Selectional Restrictions

IDHS does not provide information on selectional restrictions explicitly. It would be desirable to acquire selectional restrictions automatically, and there is some work done in this direction: acquisition from corpora [Velardi et al., 89] [Velardi et al., 91] [Grishman and Sterling, 92] and from codes already provided in machine readable dictionaries for English [Boguraev and Briscoe, 87]. There are not many publications though on the acquisition of selectional restrictions from dictionary definitions.

IDHS was constructed automatically parsing dictionary definitions, and a careful analysis of the information contained in the definitions could give clues to the processing of their representation in IDHS and the automatic acquisition of selectional restrictions. A similar approach proved successful for the acquisition of the aktionsart of English verbs [Alonge, 91]. This process could also profit from the relations already inferred in IDHS, such as synonymy, taxonomy, meronymy, etc. For instance, there is evidence that the selectional restriction information of verbs is specialized down the taxonomy [Calzolari, 90]. Finally the selectional restriction information can be integrated in the representation of IDHS.

2) Lexical-Conceptual distance

Some approaches to distance rely on semantic nets or similar kinds of Knowledge Bases. [Rada et al., 89] define conceptual distance on terms of the length of the shortest path of IS-A links between the concepts. [Sussna, 93] assigns a weight to each link and calculates the distance between two concepts as the weight of the path with minimum weight. The weights try to capture additional data. For instance, for the same path length, concepts lower in the hierarchy seem to be conceptually closer. One further approach [Resnik, 93] combines both corpus-based information-theoretic measures and the taxonomy (implemented as IS-A links) of a semantic net, defining conceptual distance, or conceptual similarity, as a function of the probability of concepts in the training corpus.

All these three approaches take into consideration that words have multiple senses. For instance, [Sussna, 93] devises his measure with the purpose of sense-disambiguating a text for indexing and text retrieval.

The knowledge representation of IDHS provides support for the experimentation of several distance measures, in order to select the most suitable for proposal discrimination. Distance measures could also profit from the other semantic relations in IDHS, as previous works rely mainly on IS-A links. [Rada et al., 89] point out that other relations could be useful, and that further work should be done in this direction. IDHS relates the concepts with a rich variety of semantic relations, such as taxonomy, meronimy or non-hierarchical relations like *theme-of*, *agent-of*, *purpose-of*, *antonymy*, etc. which should be explored.

The thesaurus of IDHS already provides a function that finds relationships between pairs of concepts, called `DRAP`. The result of this function is a path of concepts in the thesaurus labelled with semantic relations.

The kind of relations found by `DRAP` are illustrated by the following examples for french:

```
;;; Which is the relation between "couteau I 1" (knife) and
;;; "trancher I ?" (to cut a slice) ?

(drap '|couteau I 1| '|trancher I ?|)

➔   ((AND (|couteau I 1| OBJECTIF |couper I 1|)
          (|couper I 1| SYNONYMES |trancher I ?|)))
```
[6]

```
;;; Which is the relation between "gazeux I 1" (gaseous) and
;;; "liquide I ?" (liquid) ?

(drap '|gazeux I 1| '|liquide I ?|)

➔   ((AND (|gazeux I 1| CARACTERISTIQUE+INV |vapeur I 2|)
          (|vapeur I 2| CARACTERISTIQUE |liquide I ?|)))
```
[7]

---

[6] Roughly paraphrased as "the purpose of `couteau` is `couper` (to cut) which is a synonym of `trancher`".

[7] Roughly paraphrased as "`gazeux` is a feature of `vapeur` (vapour) which has as feature `liquide`".

```
;;; Which is the relation between "quart I 3" (a beaker of 1/4
;;; l. of capacity) and "vin I 1" (wine)?

(drap '|quart I 3| '|vin I 1|)

➔    ((AND (|quart I 3| OBJECTIF |boire I ?|)
           (|boire I ?| THEME |boisson I 1|)
           (|boisson I 1| HYPONYME |vin I 1|)))
```
[8]

5 CONCLUSIONS

The analysis of the corpus confirms that semantic discrimination of proposals is necessary if automatic error correction based in linguistic knowledge is to be obtained, as syntactic discrimination could only succeed maximun 70% of the times, given that all the sentences in the text were completely analyzed.

Both semantic techniques, selectional restriction and semantic distance, can profit from IDHS, which offers a good platform for the acquisition of the former, and the possibility to explore different algorithms for the later.

It has to be noted that a system with the ability to correct automatically spelling errors based on linguistic knowledge, can be also applied to perform automatic error correction in other fields where language is the support of the data, e.g. optical character recognition, text-to-speech systems and speech recognition.

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[8] Roughly paraphrased as "the purpose of `quart` is to `boire` (to drink); the theme of `boire` is `boisson` (drink as a noun) and `vin` is a kind of `boisson`".

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Towards a single proposal in spelling correction

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Abstract

The study presented here relies on the integrated use of different kinds of knowledge in order to improve first-guess accuracy in non-word context-sensitive correction for general unrestricted texts. State of the art spelling correction systems, e.g. *ispell*, apart from detecting spelling errors, also assist the user by offering a set of candidate corrections that are close to the misspelled word. Based on the correction proposals of *ispell*, we built several guessers, which were combined in different ways. Firstly, we evaluated all possibilities and selected the best ones in a corpus with artificially generated typing errors. Secondly, the best combinations were tested on texts with genuine spelling errors. The results for the latter suggest that we can expect automatic non-word correction for *all* the errors in a free running text with 80% precision and a single proposal 98% of the times (1.02 proposals on average).

Introduction

The problem of devising algorithms and techniques for automatically correcting words in text remains a research challenge. Existing spelling correction techniques are limited in their scope and accuracy. Apart from detecting spelling errors, many programs assist users by offering a set of candidate corrections that are close to the misspelled word. This is true for most commercial word-processors as well as the Unix-based spelling-corrector *ispell*[1] (1993). These programs tolerate lower first guess accuracy by returning multiple guesses, allowing the user to make the final choice of the intended word. In contrast, some applications will require fully automatic correction for general-purpose texts (Kukich 1992).

It is clear that context-sensitive spelling correction offers better results than isolated-word error correction. The underlying task is to determine the relative degree of well formedness among alternative sentences (Mays et al. 1991). The question is what kind of knowledge (lexical, syntactic, semantic, ...) should be represented, utilised and combined to aid in this determination.

This study relies on the integrated use of three kinds of knowledge (syntagmatic, paradigmatic and statistical) in order to improve first guess accuracy in non-word context-sensitive correction for general unrestricted texts. Our techniques were applied to the corrections posed by *ispell*. Constraint Grammar (Karlsson et al. 1995) was chosen to represent syntagmatic knowledge. Its use as a part of speech tagger for English has been highly successful. Conceptual Density (Agirre and Rigau 1996) is the paradigmatic component chosen to discriminate semantically among potential noun corrections. This technique measures "affinity distance" between nouns using Wordnet (Miller 1990). Finally, general and document word-occurrence frequency-rates complete the set of knowledge sources combined. We knowingly did not use any model of common misspellings, the main reason being that we did not want to use knowledge about the error source. This work focuses on language models, not error models (typing errors, common misspellings, OCR mistakes, speech recognition mistakes, etc.).

The system was evaluated against two sets of texts: artificially generated errors from the Brown corpus (Francis and Kucera 1967) and genuine spelling errors from the Bank of English[2].

The remainder of this paper is organised as follows. Firstly, we present the techniques that

[1] *Ispell* was used for the spell-checking and correction candidate generation. Its assets include broad-coverage and excellent reliability.

[2] http://titania.cobuild.collins.co.uk/boe_info.html

will be evaluated and the way to combine them. Section 2 describes the experiments and shows the results, which are evaluated in section 3. Section 4 compares other relevant work in context sensitive correction.

1 The basic techniques

1.1 Constraint Grammar (CG)

Constraint Grammar was designed with the aim of being a language-independent and robust tool to disambiguate and analyse unrestricted texts. CG grammar statements are close to real text sentences and directly address parsing problems such as ambiguity. Its application to English (ENGCG[3]) resulted a very successful part of speech tagger for English. CG works on a text where all possible morphological interpretations have been assigned to each word-form by the ENGTWOL morphological analyser (Voutilainen and Heikkilä 1995). The role of CG is to apply a set of linguistic constraints that discard as many alternatives as possible, leaving at the end almost fully disambiguated sentences, with one morphological or syntactic interpretation for each word-form. The fact that CG tries to leave a unique interpretation for each word-form makes the formalism adequate to achieve our objective.

Application of Constraint Grammar

The text data was input to the morphological analyser. For each unrecognised word, *ispell* was applied, placing the morphological analyses of the correction proposals as alternative interpretations of the erroneous word (see example 1). EngCG-2 morphological disambiguation was applied to the resulting texts, ruling out the correction proposals with an incompatible POS (cf. example 2). We must note that the broad coverage lexicons of *ispell* and ENGTWOL are independent. This caused the correspondence between unknown words and *ispell*'s proposals not to be one to one with those of the EngCG-2 morphological analyser, especially in compound words. Such problems were solved considering that a word was correct if it was covered by any of the lexicons.

1.2 Conceptual Density (CD)

The discrimination of the correct category is unable to distinguish among readings belonging to the same category, so we also applied a word-sense disambiguator based on Wordnet, that had already been tried for nouns on free-running text. In our case it would choose the correction proposal semantically closer to the surrounding context. It has to be noticed that Conceptual Density can only be applied when all the proposals are categorised as nouns, due to the structure of Wordnet.

<our>
"our" PRON PL ...
<bos> ; *INCORRECT OR SPELLING ERROR*
"boss" N S
"boys" N P
"bop" V S
"Bose" <Proper>

Example 1. Proposals and morphological analysis for the misspelling *bos*

<our>
"our" PRON PL ...
<bos> ; *INCORRECT OR SPELLING ERROR*
"boss" N S
"boys" N P
~~"bop" V S~~
"Bose" <Proper>
<are> ...

Example 2. CG leaves only nominal proposals

1.3 Frequency statistics (DF & BF)

Frequency data was calculated as word-form frequencies obtained from the document where the error was obtained (Document frequency, DF) or from the rest of the documents in the whole Brown Corpus (Brown frequency, BF). The experiments proved that word-forms were better suited for the task, compared to frequencies on lemmas.

1.4 Other interesting heuristics (H1, H2)

We eliminated proposals beginning with an uppercase character when the erroneous word did not begin with uppercase and there were alternative proposals beginning with lowercase. In example 1, the fourth reading for the misspelling "bos" was eliminated, as "Bose" would be at an editing distance of two from the misspelling (heuristic H1). This heuristic proved very reliable, and it was used in all experiments. After obtaining the first results, we also noticed that words with less than 4 characters like "si", "teh", ... (misspellings for "is" and "the") produced too many proposals, difficult to disambiguate. As they were one of the main error sources for our method, we also evaluated the results excluding them (heuristic H2).

[3] A recent version of ENGCG, known as EngCG-2, can be tested at http://www.conexor.fi/analysers.html

1.5 Combination of the basic techniques using votes

We considered all the possible combinations among the different techniques, e.g. CG+BF, BF+DF, and CG+DF. The weight of the vote can be varied for each technique, e.g. CG could have a weight of 2 and BF a weight of 1 (we will represent this combination as CG2+BF1). This would mean that the BF candidate(s) will only be chosen if CG does not select another option or if CG selects more than one proposal. Several combinations of weights were tried. This simple method to combine the techniques can be improved using optimization algorithms to choose the best weights among fractional values. Nevertheless, we did some trials weighting each technique with its expected precision, and no improvement was observed. As the best combination of techniques and weights for a given set of texts can vary, we separated the error corpora in two, trying all the possibilities on the first half, and testing the best ones on the second half (c.f. section 2.1).

2 The experiments

Based on each kind of knowledge, we built simple guessers and combined them in different ways. In the first phase, we evaluated all the possibilities and selected the best ones on part of the corpus with artificially generated errors. Finally, the best combinations were tested against the texts with genuine spelling errors.

2.1 The error corpora

We chose two different corpora for the experiment. The first one was obtained by systematically generating misspellings from a sample of the Brown Corpus, and the second one was a raw text with genuine errors. While the first one was ideal for experimenting, allowing for automatic verification, the second one offered a realistic setting. As we said before, we are testing language models, so that both kinds of data are appropriate. The corpora with artificial errors, artificial corpora for short, have the following features: a sample was extracted from SemCor (a subset of the Brown Corpus) selecting 150 paragraphs at random. This yielded a seed corpus of 505 sentences and 12659 tokens. To simulate spelling errors, a program named *antispell*, which applies Damerau's rules at random, was run, giving an average of one spelling error for each 20 words (non-words were left untouched). *Antispell* was run 8 times on the seed corpus, creating 8 different corpora with the same text but different errors. Nothing was done to prevent two errors in the same sentence, and some paragraphs did not have any error.

The corpus of genuine spelling errors, which we also call the "real" corpus for short, was magazine text from the Bank of English Corpus, which probably was not previously spell-checked (it contained many misspellings), so it was a good source of errors. Added to the difficulty of obtaining texts with real misspellings, there is the problem of marking the text and selecting the correct proposal for automatic evaluation.

As mentioned above, the artificial-error corpora were divided in two subsets. The first one was used for training purposes[4]. Both the second half and the "real" texts were used for testing.

2.2 Data for each corpora

The two corpora were passed trough *ispell*, and for each unknown word, all its correction proposals were inserted. Table 1 shows how, if the misspellings are generated at random, 23.5% of them are real words, and fall out of the scope of this work. Although we did not make a similar counting in the real texts, we observed that a similar percentage can be expected.

	1st half	2nd half	"real"
words	47584	47584	39733
errors	1772	1811	-[5]
non real-word errors	1354	1403	369
ispell proposals	7242	8083	1257
words with multiple proposals	810	852	158
long word errors (H2)	968	980	331
proposals for long words (H2)	2245	2313	807
long word errors (H2) with multiple proposals	430	425	124

Table 1. Number of errors and proposals

For the texts with genuine errors, the method used in the selection of the misspellings was the following: after applying *ispell*, no correction was found for 150 words (mainly proper nouns and foreign words), and there were about 300 which were formed by joining two consecutive words or by special affixation rules (*ispell* recognised them

4 In fact, there is no training in the statistical sense. It just involves choosing the best alternatives for voting.

5 As we focused on non-word words, there is not a count of real-word errors.

	Cover.%	Prec.%	#prop.
Basic techniques			
random baseline	100.00	54.36	1.00
random+H2	71.49	71.59	1.00
CG	99.85	86.91	2.33
CG+H2	71.42	95.86	1.70
BF	96.23	86.57	1.00
BF+H2	68.69	92.15	1.00
DF	90.55	89.97	1.02
DF+H2	62.92	96.13	1.01
CD	6.06	79.27	1.01
Combinations			
CG1+DF2	99.93	90.39	1.17
CG1+DF2+H2	71.49	96.38	1.12
CG1+DF1+BF1	99.93	89.14	1.03
CG1+DF1+BF1+H2	71.49	94.73	1.03
CG1+DF1+BF1+CD1	99.93	89.14	1.02
CG1+DF1+BF1+CD1+H2	71.49	94.63	1.02

Table 2. Results for several combinations (1st half)

	Cover.	Prec.	#prop
Basic techniques			
random baseline	100.00	23.70	1.00
random+H2	52.70	36.05	1.00
CG	99.75	78.09	3.23
CG+H2	52.57	90.68	2.58
BF	93.70	76.94	1.00
BF+H2	48.04	81.38	1.00
DF	84.20	81.96	1.03
DF+H2	38.48	89.49	1.03
CD	8.27	75.28	1.01
Combinations			
CG1+DF2	99.88	83.93	1.28
CG1+DF2+H2	52.70	91.86	1.43
CG1+DF1+BF1	99.88	81.83	1.04
CG1+DF1+BF1+H2	52.70	88.14	1.06
CG1+DF1+BF1+CD1	99.88	81.83	1.04
CG1+DF1+BF1+CD+H2	52.70	87.91	1.05

Table 3. Results on errors with multiple proposals (1st half)

correctly). This left 369 erroneous word-forms. After examining them we found that the correct word-form was among *ispell*'s proposals, with very few exceptions. Regarding the selection among the different alternatives for an erroneous word-form, we can see that around half of them has a single proposal. This gives a measure of the work to be done. For example, in the real error corpora, there were 158 word-forms with 1046 different proposals. This means an average of 6.62 proposals per word. If words of length less than 4 are not taken into account, there are 807 proposals, that is, 4.84 alternatives per word.

	Cover.%	Prec.%	#prop
Basic techniques			
random baseline	100.00	53.67	1.00
random+H2	69.85	71.53	1.00
DF	90.31	89.50	1.02
DF+H2	61.51	95.60	1.01
Combinations			
CG1+DF2	99.64	90.06	1.19
CG1+DF2+H2	69.85	95.71	1.22
CG1+DF1+BF1	99.64	87.77	1.03
CG1+DF1+BF1+H2	69.85	93.16	1.03
CG1+DF1+BF1+CD1	99.64	87.91	1.03
CG1+DF1+BF1+CD+H2	69.85	93.27	1.02

Table 4. Validation of the best combinations (2nd half)

	Cover.	Prec.	#pro
Basic techniques			
random baseline	100.00	23.71	1.00
random+H2	50.12	34.35	1.00
DF	84.04	81.42	1.03
DF+H2	36.32	87.66	1.04
Combinations			
CG1+DF2	99.41	83.59	1.31
CG1+DF2+H2	50.12	90.12	1.50
CG1+DF1+BF1	99.41	79.81	1.05
CG1+DF1+BF1+H2	50.12	84.24	1.06
CG1+DF1+BF1+CD1	99.41	80.05	1.05
CG1+DF1+BF1+CD1+H2	50.12	84.47	1.06

Table 5. Results on errors with multiple proposals (2nd half)

2.3 Results

We mainly considered three measures:

- coverage: the number of errors for which the technique yields an answer.
- precision: the number of errors with the correct proposal among the selected ones
- remaining proposals: the average number of selected proposals.

2.3.1 Search for the best combinations

Table 2 shows the results on the training corpora. We omit many combinations that we tried, for the sake of brevity. As a baseline, we show the results when the selection is done at random. Heuristic H1 is applied in all the cases, while tests are performed with and without heuristic H2. If we focus on the errors for which *ispell* generates more than one correction proposal (cf. table 3), we get a better estimate of the contribution of each guesser. There were 8.26 proposals per word in the general

	Cover. %	Prec. %	#prop.
Basic techniques			
random baseline	100.00	69.92	1.00
random+H2	89.70	75.47	1.00
CG	99.19	84.15	1.61
CG+H2	89.43	90.30	1.57
DF	70.19	93.05	1.02
DF+H2	61.52	97.80	1.00
BF	98.37	80.99	1.00
BF+H2	88.08	85.54	1.00
Combinations			
CG1+DF2	100.00	87.26	1.42
CG1+DF2+H2	89.70	90.94	1.43
CG1+DF1+BF1	100.00	80.76	1.02
CG1+DF1+BF1+H2	89.70	84.89	1.02

Table 6. Best combinations ("real" corpus)

	Cover. %	Prec. %	#prop
Basic techniques			
random baseline	100.00	29.75	1.00
random+H2	76.54	34.52	1.00
CG	98.10	62.58	2.45
CG+H2	75.93	73.98	2.52
DF	30.38	62.50	1.13
DF+H2	12.35	75.00	1.05
BF	96.20	54.61	1.00
BF+H2	72.84	60.17	1.00
Combinations			
CG1+DF2	100.00	70.25	1.99
CG1+DF2+H2	76.24	75.81	2.15
CG1+DF1+BF1	100.00	55.06	1.04
CG1+DF1+BF1+H2	76.54	59.68	1.05

Table 7. Results on errors with multiple proposals ("real" corpus)

case, and 3.96 when H2 is applied. The results for all the techniques are well above the random baseline. The single best techniques are DF and CG. CG shows good results on precision, but fails to choose a single proposal. H2 raises the precision of all techniques at the cost of losing coverage. CD is the weakest of all techniques, and we did not test it with the other corpora. Regarding the combinations, CG1+DF2+H2 gets the best precision overall, but it only gets 52% coverage, with 1.43 remaining proposals. Nearly 100% coverage is attained by the H2 combinations, with highest precision for CG1+DF2 (83% precision, 1.28 proposals).

2.3.2 Validation of the best combinations

In the second phase, we evaluated the best combinations on another corpus with artificial errors. Tables 4 and 5 show the results, which agree with those obtained in 2.3.1. They show slightly lower percentages but always in parallel.

2.3.3 Corpus of genuine errors

As a final step we evaluated the best combinations on the corpus with genuine typing errors. Table 6 shows the overall results obtained, and table 7 the results for errors with multiple proposals. For the latter there were 6.62 proposals per word in the general case (2 less than in the artificial corpus), and 4.84 when heuristic H2 is applied (one more that in the artificial corpus). These tables are further commented in the following section.

3 Evaluation of results

This section reviews the results obtained. The results for the "real" corpus are evaluated first, and the comparison with the other corpora comes later. Concerning the application of each of the simple techniques separately[6]:

- Any of the guessers performs much better than random.
- DF has a high precision (75%) at the cost of a low coverage (12%). The difference in coverage compared to the artificial error corpora (84%) is mainly due to the smaller size of the documents in the real error corpus (around 50 words per document). For medium-sized documents we expect a coverage similar to that of the artificial error corpora.
- BF offers lower precision (54%) with the gains of a broad coverage (96%).
- CG presents 62% precision with nearly 100% coverage, but at the cost of leaving many proposals (2.45)
- The use of CD works only with a small fraction of the errors giving modest results. The fact that it was only applied a few times prevents us from making further conclusions.

Combining the techniques, the results improve:

- The CG1+DF2 combination offers the best results in coverage (100%) and precision (70%) for all tests. As can be seen, CG raises the coverage of the DF method, at the cost of also increasing the number of proposals (1.9) per erroneous word. Had the coverage of DF increased, so would also the number of

[6] If not explicitly noted, the figures and comments refer to the "real" corpus, table 7.

proposals decrease for this combination, for instance, close to that of the artificial error corpora (1.28).

- The CG1+DF1+BF1 combination provides the same coverage with nearly one interpretation per word, but decreasing precision to a 55%.
- If full coverage is not necessary, the use of the H2 heuristic raises the precision at least 4% for all combinations.

When comparing these results with those of the artificial errors, the precisions in tables 2, 4 and 6 can be misleading. The reason is that the coverage of some techniques varies and the precision varies accordingly. For instance, coverage of DF is around 70% for real errors and 90% for artificial errors, while precisions are 93% and 89% respectively (cf. tables 6 and 2). This increase in precision is not due to the better performance of DF[7], but can be explained because the lower the coverage, the higher the proportion of errors with a single proposal, and therefore the higher the precision.

The comparison between tables 3 and 7 is more clarifying. The performance of all techniques drops in table 7. Precision of CG and BF drops 15 and 20 points. DF goes down 20 points in precision and 50 points in coverage. This latter degradation is not surprising, as the length of the documents in this corpus is only of 50 words on average. Had we had access to medium sized documents, we would expect a coverage similar to that of the artificial error corpora.

The best combinations hold for the "real" texts, as before. The highest precision is for CG1+DF2 (with and without H2). The number of proposals left is higher in the "real" texts than in the artificial ones (1.99 to 1.28). It can be explained because DF does not manage to cover all errors, and that leaves many CG proposals untouched.

We think that the drop in performance for the "real" texts was caused by different factors. First of all, we already mentioned that the size of the documents strongly affected DF. Secondly, the nature of the errors changes: the algorithm to produce spelling errors was biased in favour of frequent words, mostly short ones. We will have to analyse this question further, specially regarding the origin of the natural errors. Lastly, BF was trained on the Brown corpus on American English, while the "real" texts come from the Bank of English. Presumably, this could have also affected negatively the performance of these algorithms.

Back to table 6, the figures reveal which would be the output of the correction system. Either we get a single proposal 98% of the times (1.02 proposals left on average) with 80% precision for all non-word errors in the text (CG1+DF1+BF1) or we can get a higher precision of 90% with 89% coverage and an average of 1.43 proposals (CG1+DF2+H2).

4 Comparison with other context-sensitive correction systems

There is not much literature about automatic spelling correction with a single proposal. Menezo et al. (1996) present a spelling/grammar checker that adjusts its strategy dynamically taking into account different lexical agents (dictionaries, ...), the user and the kind of text. Although no quantitative results are given, this is in accord with using document and general frequencies.

Mays et al. (1991) present the initial success of applying word trigram conditional probabilities to the problem of context based detection and correction of real-word errors.

Yarowsky (1994) experiments with the use of decision lists for lexical ambiguity resolution, using context features like local syntactic patterns and collocational information, so that multiple types of evidence are considered in the context of an ambiguous word. In addition to word-forms, the patterns involve POS tags and lemmas. The algorithm is evaluated in missing accent restoration task for Spanish and French text, against a predefined set of a few words giving an accuracy over 99%.

Golding and Schabes (1996) propose a hybrid method that combines part-of-speech trigrams and context features in order to detect and correct real-word errors. They present an experiment where their system has substantially higher performance than the grammar checker in MS Word, but its coverage is limited to eighteen particular confusion sets composed by two or three similar words (e.g.: weather, whether).

The last three systems rely on a previously collected set of confusion sets (sets of similar words or accentuation ambiguities). On the contrary, our system has to choose a single

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[7] In fact the contrary is deduced from tables 3 and 7.

proposal for any possible spelling error, and it is therefore impossible to collect the confusion sets (i.e. sets of proposals for each spelling error) beforehand. We also need to correct as many errors as possible, even if the amount of data for a particular case is scarce.

Conclusion

This work presents a study of different methods that build on the correction proposals of *ispell*, aiming at giving a single correction proposal for misspellings. One of the difficult aspects of the problem is that of testing the results. For that reason, we used both a corpus with artificially generated errors for training and testing, and a corpus with genuine errors for testing.

Examining the results, we observe that the results improve as more context is taken into account. The word-form frequencies serve as a crude but helpful criterion for choosing the correct proposal. The precision increases as closer contexts, like document frequencies and Constraint Grammar are incorporated. From the results on the corpus of genuine errors we can conclude the following. Firstly, the correct word is among *ispell*'s proposals 100% of the times, which means that all errors can be recovered. Secondly, the expected output from our present system is that it will correct automatically the spelling errors with either 80% precision with full coverage or 90% precision with 89% coverage and leaving an average of 1.43 proposals.

Two of the techniques proposed, Brown Frequencies and Conceptual Density, did not yield useful results. CD only works for a very small fraction of the errors, which prevents us from making further conclusions.

There are reasons to expect better results in the future. First of all, the corpus with genuine errors contained very short documents, which caused the performance of DF to degrade substantially. Further tests with longer documents should yield better results. Secondly, we collected frequencies from an American English corpus to correct British English texts. Once this language mismatch is solved, better performance should be obtained. Lastly, there is room for improvement in the techniques themselves. We knowingly did not use any model of common misspellings. Although we expect limited improvement, stronger methods to combine the techniques can also be tried.

Continuing with our goal of attaining a single proposal as reliably as possible, we will focus on short words and we plan to also include more syntactic and semantic context in the process by means of collocational information. This step opens different questions about the size of the corpora needed for accessing the data and the space needed to store the information.

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"Towards a single proosal in spelling sorrection"

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Title:

Towards a single proposal in spelling correction

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Abstract:

The study here presented relies on the integrated use of three kinds of knowledge (syntagmatic, paradigmatic and statistical) in order to improve first-guess accuracy in non-word context-sensitive correction for general unrestricted texts. State of the art spelling correction systems, e.g. *ispell*, in addition to detecting spelling errors also assist the user by offering a set of candidate corrections that are close to the misspelled word. Based on the correction proposals of *ispell*, we built several guessers which were combined in different ways. Firstly, we evaluated all the possibilities and selected the best ones on a corpus with artificially generated typing errors. Secondly, the best combinations were tested on texts containing genuine spelling errors. The results for the latter suggest that we can expect automatic non-word correction for *all* the errors in a free-running text with 90% precision and a single proposal 24 times out of 25 (1.04 proposals on average).

Topic areas:

spelling correction

Towards a single proposal in spelling correction

Abstract

The study here presented relies on the integrated use of three kinds of knowledge (syntagmatic, paradigmatic and statistical) in order to improve first-guess accuracy in non-word context-sensitive correction for general unrestricted texts. State of the art spelling correction systems, e.g. *ispell*, in addition to detecting spelling errors also assist the user by offering a set of candidate corrections that are close to the misspelled word. Based on the correction proposals of *ispell*, we built several guessers which were combined in different ways. Firstly, we evaluated all the possibilities and selected the best ones on a corpus with artificially generated typing errors. Secondly, the best combinations were tested on texts containing genuine spelling errors. The results for the latter suggest that we can expect automatic non-word correction for *all* the errors in a free-running text with 90% precision and a single proposal 24 times out of 25 (1.04 proposals on average).

Introduction

The problem of devising algorithms and techniques for automatically correcting words in text remains being a research challenge. Existing spelling correction techniques are limited in their scope and accuracy. In addition to detecting spelling errors many programs assist users by offering a set of candidate corrections that are close to the misspelled word. This is true for most of the commercial word-processors as well as the Unix-based spelling-corrector *ispell*[1] (1993). These programs tolerate lower first guess accuracy by returning multiple guesses and allowing the user to make the final choice of the intended word. In contrast, some applications will require fully automatic correction for general purpose texts (Kukich 1992).

It is clear that context-sensitive correction will offer better results than isolated-word error correction. The task underlying context-sensitive spelling correction is to determine the relative degree of well-formedness among alternative sentences (Mays et al. 1991). The question is what kind of knowledge (lexical, syntactic, semantic, statistical, ...) should be represented, utilised and combined to aid in this determination.

The study here presented relies on the integrated use of three kinds of knowledge (syntagmatic, paradigmatic and statistical) in order to improve first guess accuracy in nonword context-sensitive correction for general unrestricted texts. Our techniques were applied on the corrections posed by *ispell*. Constraint Grammar (Karlsson 1995) was chosen to represent syntagmatic knowledge. Its use as a part of speech tagger for English was completely successful. Conceptual Density (Agirre and Rigau 1997) is the paradigmatic component chosen to discriminate semantically among potential noun corrections. This technique measures "affinity distance" between nouns using Wordnet (Miller 1990). Information on affinity to context was also collected from corpora, in the form of collocational and cooccurrence statistical features (Yarowsky 1994). Finally, general and document word-occurrence frequency-rates complete the set of different knowledge sources combined in the system. We knowingly did not use any model of common misspellings, the main reason being that we did not want to use knowledge about the error source. This work focuses on language models, not error models (typing errors, common misspellings, OCR mistakes, speech recognition mistakes, etc.).

The system was evaluated on two sets of texts: artificially generated typing errors from the

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[1] Ispell was used for the spell-checking and correction candidate generation. Its assets include broad-coverage, excellent reliability (cf. the conclusion) and the fact that it is able to produce several kinds of output, e.g. errors and proposals only.

Brown corpus (Francis & Kucera 1967) and genuine spelling errors from the Bank of English[2].

The remainder of this paper is organised as follows. Firstly, we present the techniques that will be evaluated and the way to combine them. Section 2 describes the experiments performed and shows the results, which are evaluated in section 3. Section 4 compares other relevant work in context sensitive correction. Finally, the paper ends with some concluding remarks.

1 The basic techniques

1.1 Constraint Grammar (CG)

Constraint Grammar was designed with the aim of being a language-independent and robust tool to disambiguate and analyse unrestricted texts. The CG grammar statements are close to real text sentences and directly address some notorious parsing problems, especially ambiguity. Its application to English (ENGCG) is a very successful part of speech tagger for English.

These are four major steps in the CG morphosyntactic treatment of texts: morphological analysis, morphological disambiguation, determination of clause boundaries and the assignment of syntactic functions. CG works on a text where all the possible morphological interpretations have been assigned to each word-form by the ENGTWOL morphological analyser (Koskenniemi 1983). The basic parsing strategy is to profit from the existing morphological information. Every relevant structure is assigned directly via lexicon, morphology and mappings from morphology to syntax. The role of CG is to apply a set of linguistic constraints that discard as many alternatives as possible, leaving at the end almost fully disambiguated sentences, with one morphological/syntactic interpretation for each word-form. The fact that CG tries to leave a unique morphological/syntactic interpretation for each word-form makes this formalism adequate to achieve our objective.

[2] http://titania.cobuild.collins.co.uk/boe_info.html

Application of Constraint Grammar

The text data was input to the morphological analyser (ENGTWOL). For each unrecognised word *ispell* was applied, placing the morphological analyses of the correction proposals as alternative interpretations of the erroneous word (see Example 1).

<our>
  "our" PRON PL ...
<bos> ; *INCORRECT OR SPELLING ERROR*
  "boss" N S
  "boys" N P
  "bop" V S
  "Bose" <Proper>
<are> ...

Example 1.
Proposals and morphological analysis for the misspelling *bos*.

The CG morphological disambiguation was applied on the resulting texts, ruling out the correction proposals with an incompatible POS (cf. example 2).

<our>
  "our" PRON PL ...
<bos> ; *INCORRECT OR SPELLING ERROR*
  "boss" N S
  "boys" N P
  ~~"bop" V S~~
  "Bose" <Proper>
<are> ...

Example 2.
CG leaves only nominal proposals.

We have to note that the broad coverage lexicons of *ispell* and ENGTWOL are independent. This caused the correspondence between unknown words and the proposals given by *ispell* not to be one to one with those of the ENGTWOL lexicon, especially in compound words. Such problems were solved considering that a word was correct if it was covered by any of the lexicons.

1.2 Conceptual Density (CD)

The discrimination of the correct category is unable to distinguish among readings belonging to the same category, so that we also applied a word-sense disambiguator (Agirre & Rigau 1996) based on Wordnet to this task. The word-sense disambiguator had already been tried for nouns on free-running text. In our case the disambiguator would choose the correction proposal semantically closer to the surrounding context. It has to be noted that Conceptual Density can only be applied whenever all the proposals are categorised as nouns.

1.3 Frequency statistics (DF & BF)

Frequency data was calculated as word-form frequencies obtained from the document where the error was obtained (Document frequency, DF) or from the rest of the documents in the whole Brown Corpus (Brown frequency, BF). The experiments proved that word-forms were better suited for the task, compared to frequencies on lemmas.

1.4 Context statistics (CX)

In accordance to the proposals of (Yarowsky 1994), we modelled the lexical preference of the proposals. Context features were collected for all the words in the Brown Corpus (minus the test documents). The collected features were:

- word bigrams
- word trigrams
- context words in a ±20 word-window

When processing an error, the features for each proposal were retrieved and their weight measured using log-likelihood (Yarowsky 1994). The proposal with the strongest feature would be chosen, under the supposition that it would be the best fitted for the context of the error.

1.5 Other interesting heuristics (H1, H2)

We eliminated proposals beginning with an uppercase character when the erroneous word did not begin with an uppercase letter and there were alternative proposals beginning with lowercase. In example 1 of the previous section, the fourth reading for the misspelling "bos" was eliminated, as "Bose" would be at an editing distance of two from the misspelling (heuristic H1). This heuristic proved very reliable, and it was used in all experiments.

After obtaining the first results, we also noted that words with less than 4 characters like "si", "teh", ... (misspellings for "is" and "the") produced too many proposals, difficult to disambiguate. As they were one of the main error sources for our method, we also evaluated the results excluding them (heuristic H2).

1.6 Combination of the basic techniques using votes

We considered all the possible combinations among the different techniques e.g. CG+BF, BF+DF, CG+DF+CX, etc.

The weight of the vote can be varied for each technique, e.g. CG could have a weight of 2 and BF a weight of 1 (we will represent this combination as CG2+BF1). This would mean that the BF candidate(s) will only be chosen if CG does not select another option. Several combinations of weights were tried.

As the best combination of techniques and weights for a given set of texts can vary we separated the error corpora in two, trying all the possibilities on the first half, and testing the performance of the best ones on the second half (c.f. section 2.1).

This simple method to combine the techniques can be improved using optimization algorithms to choose the best weigths among fractional values. Nevertheless, we did some trials weighting each technique with its expected precision and no imprevement was observed.

2 The experiments

Based on each kind of knowledge we built a simple guesser, and combined them in different ways. In a first phase, we evaluated all the possibilities and selected the best ones on a part of the corpus with artificially generated typing errors. Finally, the best combinations were tested on the texts with genuine spelling errors.

2.1 The error corpora

As we have explained before, we chose two different corpora for the experiment. The first one was obtained by systematically generating misspellings from a sample of the Brown Corpus, and the second one was a raw text with genuine errors. While the first one was ideal for experimenting with different parameters, allowing for automatic verification, the second offered a realistic setting.

The corpora with artificial errors, artificial corpora for short, have the following features: a sample was extracted from SemCor (a subset of the Brown Corpus) selecting 150 paragraphs at random. This yielded a seed corpus of 505 sentences and 12659 tokens. To simulate spelling errors a program named *antispell* which applies Damerau's rules at random was run, creating an average of one spelling error for each 20 words (nonwords were left untouched). *Antispell* was run 8 times on the seed corpus, creating 8 different corpus with the same text but different errors. Nothing was done to prevent two errors in the same sentence, and some paragraphs did not have any error.

The corpus of genuine spelling errors, which we also call the "real" corpus for short, was magazine text from the Bank of English Corpus, which was not previously spell-checked. Added to the difficulty of obtaining texts with real misspellings there is the problem of marking the text and selecting the correct proposal for automatic evaluation.

As mentioned above, the artificial-error corpora were divided in two subsets. The first one is composed of the first half, i.e. sets 1, 2, 3 and 4. It was used for training purposes[3]. The second half comprises texts 5, 6, 7 and 8. Both the second half and the "real" texts were used for testing.

2.2 Data for each corpora

The two corpora were passed trough *ispell*, and for each unknown word all its correction proposals were inserted.

Table 1 shows how, if the misspellings are generated at random, 23.5% of them are real words, and fall out of the scope of this work. Although we did not made a similar counting in the real texts, we observed that a similar percentage can be expected.

	1st half	2nd half	"real"
words	47584	47584	39733
errors	1772	1811	-[4]
non real-word errors	1354	1403	369
ispell proposals	7242	8083	1257
words with multiple proposals	810	852	158
long word errors (H2)	968	980	331
proposals for long words (H2)	2245	2313	807
long word errors (H2) with multiple proposals	430	425	124

Table 1. Number of errors and proposals

For the texts with genuine errors, the method used in the selection of the misspellings was the following: after applying *ispell*, no correction was found for 150 words (mainly proper nouns and foreign words), and there were about 300 which were formed by joining two consecutive words or by special affixation rules (*ispell* recognised them correctly most of the times). This left 369 erroneous word-forms. After examining them we found that the correct word-form was, with very few exceptions, among *ispell*'s proposals.

Regarding the selection among the different alternatives for an erroneous word-form, we see that around half of them have a single proposal. This gives a measure of the work to be done. For example, in the real error corpora, there were 158 word-forms with 1046 different proposals. This means an average of 6.62 proposals per word. If words of length less than 4 are not taken into account, there are 807 proposals, that is, 4.84 alternatives per word.

[3] In fact, there is no training in the statistical sense, but it is rather choosing the best alternatives for voting (cf. 1.6).

[4] As we focused on unknown words, there is not a count of real-word errors.

	cover. %	prec. %	#prop.
Basic techniques			
random baseline	100.00	54.36	1.00
random+H2	71.49	71.59	1.00
CG	99.85	86.91	2.33
CG+H2	71.42	95.86	1.70
BF	96.23	86.57	1.00
BF+H2	68.69	92.15	1.00
DF	90.55	89.97	1.02
DF+H2	62.92	96.13	1.01
CX	96.70	91.20	1.01
CX+H2	68.54	95.70	1.01
CD	6.06	79.27	1.01
Combinations			
CG1+DF2	99.93	90.39	1.17
CG1+DF2+H2	71.49	96.38	1.12
CG1+DF1+BF1	99.93	89.14	1.03
CG1+DF1+BF1+H2	71.49	94.73	1.03
CG1+DF1+BF1+CD1	99.93	89.14	1.02
CG1+DF1+BF1+CD1+H2	71.49	94.63	1.02
CG1+DF1+CX1	99.93	91.90	1.07
CG1+DF1+CX1+H2	71.49	96.50	1.05
CG1+DF1+CX2	99.93	91.30	1.04
CG1+DF1+CX2+H2	71.49	95.70	1.04

Table 2. Results for several combinations (1st half)

	Cover. %	Prec. %	#prop
Basic techniques			
random baseline	100.00	23.70	1.00
random+H2	52.70	36.05	1.00
CG	99.75	78.09	3.23
CG+H2	52.57	90.68	2.58
BF	93.70	76.94	1.00
BF+H2	48.04	81.38	1.00
DF	84.20	81.96	1.03
DF H2	38.48	89.49	1.03
CX	94.48	84.94	1.02
CX+H2	47.79	89.77	1.02
CD	8.27	75.28	1.01
Combinations			
CG1+DF2	99.88	83.93	1.28
CG1+DF2+H2	52.70	91.86	1.43
CG1+DF1+BF1	99.88	81.83	1.04
CG1+DF1+BF1+H2	52.70	88.14	1.06
CG1+DF1+BF1+CD1	99.88	81.83	1.04
CG1+DF1+BF1+CD+H2	52.70	87.91	1.05
CG1+DF1+CX1	99.88	86.45	1.12
CG1+DF1+CX1+H2	52.70	92.12	1.11
CG1+DF1+CX2	99.88	85.45	1.07
CG1+DF1+CX2+H2	52.70	90.32	1.09

Table 3. Results on errors with multiple proposals (1st half)

	cover. %	Prec.%	#prop.
Basic techniques			
Random baseline	100.00	53.67	1.00
Random+H2	69.85	71.53	1.00
DF	90.31	89.50	1.02
DF H2	61.51	95.60	1.01
CX	97.20	91.00	1.01
CX+H2	67.93	94.30	1.01
Combinations			
CG1+DF2	99.64	90.06	1.19
CG1+DF2+H2	69.85	95.71	1.22
CG1+DF1+BF1	99.64	87.77	1.03
CG1+DF1+BF1+H2	69.85	93.16	1.03
CG1+DF1+BF1+CD1	99.64	87.91	1.03
CG1+DF1+BF1+CD+H2	69.85	93.27	1.02
CG1+DF1+CX1	99.71	91.60	1.09
CG1+DF1+CX1+H2	69.85	95.10	1.07
CG1+DF1+CX2	99.71	91.07	1.04
CG1+DF1+CX2+H2	69.85	94.18	1.03

Table 4. Validation of the best combinations (2nd half)

	Cover. %	Prec. %	#prop
Basic techniques			
random baseline	100.00	23.71	1.00
random+H2	50.12	34.35	1.00
DF	84.04	81.42	1.03
DF H2	36.32	87.66	1.04
CX	95.39	84.90	1.02
CX H2	46.93	86.35	1.02
Combinations			
CG1+DF2	99.41	83.59	1.31
CG1+DF2+H2	50.12	90.12	1.50
CG1+DF1+BF1	99.41	79.81	1.05
CG1+DF1+BF1+H2	50.12	84.24	1.06
CG1+DF1+BF1+CD1	99.41	80.05	1.05
CG1+DF1+BF1+CD+H2	50.12	84.47	1.06
CG1+DF1+CX1	99.53	86.14	1.15
CG1+DF1+CX1+H2	50.12	88.70	1.16
CG1+DF1+CX2	99.53	85.26	1.07
CG1+DF1+CX2+H2	50.12	86.59	1.07

Table 5. Results on errors with multiple proposals (2nd half)

2.3 Results

There are three measures which we deemed important:

- coverage: the number of errors for which the technique yields an answer.
- precision: the number of errors for which the correct proposal remains among the selected ones

- remaining proposals: the average number of selected proposals.

2.3.1 Search for the best combinations

Table 2 shows some of the results obtained for the training corpora (1st half of the corpora with artificial errors), with the most interesting results shadowed. We omit most of the combinations we tried for the sake of brevity. As a baseline, we show the results when the selection is done at random. Heuristic H1 is applied in all of the cases, while tests are performed with and without heuristic H2.

If we focus on the errors for which *ispell* generates more than one correction proposal (cf. table 3), we can get a better estimate of the contribution of each guesser. There were 8.26 proposals per word in the general case, and 3.96 when heuristic H2 is applied. The results for all the techniques are well above the random baseline. The single best techniques are DF and CX. CG has also good results on precision, but fails to choose a single proposal. The H2 heuristic raises the precision of all techniques at least 5 points, at the cost of losing coverage. CD is the weakest of all techniques, and we did not test it with the other corpora.

Regarding the combinations, CG+DF+CX+H2 gets the best precision overall, but only gets 52% coverage. CG1+DF2+H2 follows close, with more proposals. Nearly 100% coverage is attained by the combinations without H2, with highest precision for CG+DF+CX (86% precision, 1.12 proposals). If CX gets double votes (CG1+DF1+CX2) fewer proposals are selected (1.07) but one point is lost in precision.

2.3.2 Validation of the best combinations

In the second phase, we evaluated the best combinations on another corpus with artificially generated typing errors. Tables 4 and 5 show that the results for the 2nd half agree with those obtained in 2.3.1. The results show slightly lower percentages for all techniques, but always in parallel. This confirms that the best combinations hold for other texts.

	Cover. %	prec. %	#prop.
Basic techniques			
random baseline	100.00	69.92	1.00
random+H2	89.70	75.47	1.00
CG	99.19	84.15	1.61
CG+H2	89.43	90.30	1.57
DF	70.19	93.05	1.02
DF+H2	61.52	97.80	1.00
BF	98.37	80.99	1.00
BF+H2	88.08	85.54	1.00
CX	97.02	89.10	1.02
CX+H2	85.64	91.50	1.01
Combinations			
CG1+DF2	100.00	87.26	1.42
CG1+DF2+H2	89.70	90.94	1.43
CG1+DF1+BF1	100.00	80.76	1.02
CG1+DF1+BF1+H2	89.70	84.89	1.02
CG1+DF1+CX1	100.00	90.80	1.24
CG1+DF1+CX1+H2	89.70	93.10	1.20
CG1+DF1+CX2	100.00	89.70	1.04
CG1+DF1+CX2+H2	89.70	91.80	1.03

Table 6. Best combinations ("real" corpus)

	cover. %	prec. %	#prop
Basic techniques			
random baseline	100.00	29.75	1.00
random+H2	76.54	34.52	1.00
CG	98.10	62.58	2.45
CG+H2	75.93	73.98	2.52
DF	30.38	62.50	1.13
DF+H2	12.35	75.00	1.05
BF	96.20	54.61	1.00
BF+H2	72.84	60.17	1.00
CX	93.21	74.16	1.05
CX+H2	67.28	75.36	1.03
Combinations			
CG1+DF2	100.00	70.25	1.99
CG1+DF2+H2	76.24	75.81	2.15
CG1+DF1+BF1	100.00	55.06	1.04
CG1+DF1+BF1+H2	76.54	59.68	1.05
CG1+DF1+CX1	100.00	78.51	1.56
CG1+DF1+CX1+H2	76.54	81.58	1.53
CG1+DF1+CX2	100.00	75.94	1.09
CG1+DF1+CX2+H2	76.54	78.11	1.08

Table 7. Results on errors with multiple proposals ("real" corpus)

2.3.3 Corpus of genuine errors

As a final step we evaluated the best combinations on the corpus with genuine typing errors. Table 6 shows the overall results obtained, and table 7 the results for errors with multiple proposals. For the latter there were 6.62

proposals per word in the general case (2 less than in the artificial corpus), and 4.84 when heuristic H2 is applied (one more that in the artificial corpus).

These tables are further commented in the following section.

3 Evaluation of results

This sections reviews the results obtained. The results for the "real" texts are evaluated first, and the comparison with the other texts comes later.

Concerning the application of each of the simple techniques separately[5]:

- Any of the guessers performs much better than random.
- CX has the highest precision (74%) with 93% coverage.
- DF has lower precision (62%) and lower coverage (30%).
- BF offers lower precision (54%) with the gains of a broad coverage (96%).
- CG presents 62% precision with nearly 100% coverage, but at the cost of leaving many proposals (2.45)

When the techniques are combined, the results improve:

- The CG+DF+CX combination offers the best results in coverage (close to 100%) and precision for all tests (78% in table 7).
- If CX gets double weight, CG1+DF1+CX2, some precision is lost (76%), but the number of proposals left is more satisfactory (1.09 against 1.56).
- CG1+DF2 attains 70% precision. As it can be seen, CG raises the coverage of the DF method, at the cost of also increasing the number of proposals (1.9) per erroneous word. Had the coverage of DF increased, so would also decrease the number of proposals for this combination, for instance, close to that of the artificial error corpora (1.28).
- The CG1+DF1+BF1 combination provides the same coverage with nearly one interpretation per word, but decreasing precision to a 55%.
- If full coverage is not necessary, the use of the H2 heuristic raises the precision at least 3% for all combinations.

When comparing these results with those of the artificial errors, the precisions in tables 2, 4 and 6 can be misleading. The reason is that the coverage of some techniques varies and the precision varies accordingly. For instance, coverage of DF is around 70% for real errors and 90% for artificial errors, while precisions are 93% and 89% respectively (cf. tables 6 and 2). This raise in precision is not due to the better performance of DF[6], but can be explained because the lower the coverage the higher the proportion of errors with a single proposal, and therefore the higher the precision.

The comparison between tables 3 and 7 is more clarifying. The performance of all techniques drops in table 7. Precision of CG, CX and BF drops 15, 10 and 20 points respectively. DF goes down 20 points in precision and 50 points in coverage. This latter degradation in performance is not surprising, as the length of the documents in this corpus is only of 50 words on average. Had we used medium sized documents, we would expect a coverage similar to that of the artificial error corpora.

The best combinations hold for the "real" texts, as before. The highest precision is for CG+DF+CX (with and without H2). The number of proposals left is higher in the "real" texts than in the artificial texts (1.56 to 1.12). This can be explained because DF and CX do not manage to cover all errors, and that leaves many proposals of CG untouched.

We think that the drop in performance for the "real" texts was caused by different factors. First of all, we already mentioned that the size of the documents strongly affected DF. Secondly, the nature of the errors change: the algorithm to

[5] If not explicitly noted, the figures and comments refer to the "real" text, table 7.

[6] In fact the contrary is deduced from the data in tables 3 and 7.

produce spelling errors was biased in favour of frequent words, mostly short ones. We will have to analyze this question further, specially regarding the origin of the natural errors. Lastly, two techniques, namely BF and CX, were trained on the Brown corpus on American English, while the "real" texts come from the Bank of English. Presumably, this could have also affected negatively the performance of these algorithms.

Back to table 6, the figures reveal which would be the output of the correction system. Either we get a single proposal 24 times out of 25 (1.04 proposals left on average) with 90% precision for all non-word errors in the text (CG1+DF1+CX2) or we can get a higher precision of 93% with 90% coverage and an average of 1.20 proposals (CG+DF+CX+H2).

4 Comparing with other context-sensitive correction systems

There is not much literature about automatic spelling correction with a single proposal. Menezo et al. (1996) present the design of an interactive automatic spelling and grammar checker/corrector based on an architecture of distributed artificial intelligence and a multi-agent system. It allows to adjust its strategy dynamically taking into account the different lexical agents (dictionaries, ...), the user, the kind of text, and even the window. Although no quantitative results are given, this is in accord with using the document and general frequencies.

Mays et al. (1991) present the initial success of applying word trigram conditional probabilities to the problem of context based detection and correction of real-word errors.

Yarowsky (1994) experiments the use of decision lists for lexical ambiguity resolution, using context features (cf. section 1.4) like local syntactic patterns and collocational information, so that multiple types of evidence are considered in the context of an ambiguous word. In addition to word forms, the patterns involve part of speech tags and lemmas. The algorithm is evaluated in missing accent restoration task, in the case of restoring missing accents in Spanish and French text. It is evaluated against a predefined set of a few words giving an accuracy over 99%.

Golding and Schabes (1996) propose an hybrid method that combines part-of-speech trigrams and context features in order to detect and correct real-word errors. They present an experiment where their system has substantially higher performance than the grammar checker in Microsoft Word, but its coverage is limited to eighteen particular confusion sets composed by two or three similar words (e.g.: weather, whether).

The last three systems rely on a previously collected set of confusion sets (sets of similar words or accentuation ambiguities). On the contrary, our system has to choose a single proposal for any possible spelling error, and it is therefore impossible to collect the confusion sets (i.e. sets of proposals for each spelling error) beforehand. We also need to correct as many errors as possible, even if the amount of data for a particular case is scarce.

Conclusion

This work presents a study of different methods, which build on the correction proposals of *ispell*, aiming at giving a single correction proposal for misspellings. One of the difficult aspects of the problem is that of testing the results. For that reason, we used both a corpus with artificially generated errors for training and testing, and a corpus with genuine errors for testing.

Examining the results, we observe that the results improve as more context is taken into account. The word-form frequencies from the Brown Corpus serve as a crude but helpful criterion for choosing the correct proposal. The precision increases as closer contexts, like document frequencies, Constraint Grammar and context features are incorporated.

From the results on the corpus of genuine errors we can conclude the following. Firstly, the correct word is among *ispell*'s proposals 100% of the times, which means that all errors can be recovered. Secondly, the output that can be expected from our present system is that it will correct automatically the spelling errors with either 90% precision with full coverage and choosing a single proposal 24 times out of 25 (1.04 proposals left), or 93% precision with 90% coverage and leaving an average of 1.20 proposals.

Two of the techniques proposed, Brown Frequencies and Conceptual Density, did not yield useful results. CD only works for a very small fraction of the errors, which prevents us from making further conclusions.

There are reasons to expect better results in the future. First of all, the corpus with genuine errors contained very short documents, which caused the performance of DF to degrade substantially. Further tests with longer documents should yield better results. Secondly, we collected context features from an American English corpus which we used to correct British English texts. Once this language mismatch is solved better performance should be obtained. Lastly, there is room for improvement in the techniques themselves. We knowingly did not use any model of common misspellings. Regarding context features, only word-form features were collected, and part-of-speech and lemma features would presumably be a good complement. Although we would expect limited improvement, stronger methods to combine the techniques can also be tried.

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Disambiguating bilingual nominal entries against WordNet

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1. INTRODUCTION

One reason why the lexical capabilities of NLP systems have remained weak is because of the labour intensive nature of encoding lexical entries for the lexicon. It has been estimated that the average time needed to construct manually a lexical entry for a Machine Translation system is about 30 minutes [Neff et al. 93]. The automatic acquisition of lexical knowledge is the main field of the research work presented here. In particular, this paper explores the acquisition of conceptual knowledge from bilingual dictionaries (French/English, Spanish/English and English/Spanish) using a pre-existing broad coverage Lexical Knowledge Base (LKB) WordNet [Miller 90].

The automatic acquisition of lexical knowledge from monolingual machine-readable dictionaries (MRDs) has been broadly explored (e.g. [Boguraev & Briscoe 90], [Artola 93], [Castellón 93], [Wilks et al. 93], [Dolan et al. 93]), while less attention has been paid to bilingual dictionaries (e.g. [Ageno et al. 94], [Knight & Luk 94]).

Bilingual dictionaries contain information about the connection of vocabularies in two different languages. However, MRDs are made for human readers and the information contained in it is not immediately usable as a computational lexicon. For instance word translations are not marked with a sense or group of senses (sense mismatch problem), but they are sometimes annotated with subject field codes or cue words in the source language.

Two different, complementary approaches are explored in this paper. Both of them use WordNet to obtain a multilingual LKB (MLKB). The resulting MLKB has the same structure as WordNet, but some nodes are attached additionally to disambiguated vocabulary of other languages.

In one of the approaches each entry of the dictionary is taken in turn, exploiting the information in the entry itself. The inferential capability for disambiguating the translation is given by Semantic Density over WordNet [Agirre & Rigau, 95]. In the other approach, the bilingual dictionary was merged with WordNet, exploiting mainly synonymy relations. Each of the approaches was used in a different dictionary. The first approach was used on a French-English dictionary (using one direction only), and the second approach on a Spanish-English/English-Spanish dictionary (both directions).

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** Eneko Agirre was supported by a grant from the Basque Government.

After this short introduction, section 2 shows some experiments and results using Semantic Density on the bilingual French/English dictionary. In section 3 several complementary techniques and results using the Spanish bilingual dictionaries are explained.

2. WORD SENSE DISAMBIGUATION USING CONCEPTUAL DENSITY

2.1 The French/English bilingual dictionary

The French/English bilingual dictionary contains 21,322 entries. Each entry can comprise several or a single sense of the source word, which in the scope of this paper we will call subentries. For instance, the entry for ‘maintien’ is split in two subentries:

```
maintien n.m. (attitude) bearing; (conservation) maintenance.

maintien 1: n.m. (attitude) bearing
maintien 2: n.m. (conservation) maintenance
```

The dictionary has 31,502 such subentries, from which 16,917 are nominal subentries.

Each subentry can have the following fields: part of speech (always), semantic field (one out of a set of 20, e.g. `comm.` in `tr sor 2` in the example below), cue in French (e.g. `ressources` in `tr sor 2`) and one or several translations in English (always). The semantic field and the cue in French are used to determine the context or the usage of the French word when translated by the subentry.

```
folie 1: n.f. madness
provision 1: n.f. supply, store
tr sor 2: n.m. (ressources) (comm.) finances
```

In order to figure out which WordNet sense(s) fit(s) best the French headword, the algorithm needs contextual information (as we humans do). If we do not have any contextual information, and the translation has more than one sense, it is not possible to find the correct sense(s)[1] . The cases where we can try to disambiguate the translation are the following:

1) one of the translation words is monosemous in WordNet
2) the translation is given by a list of words
3) a cue in French is provided alongside the translation
4) a semantic field is provided

From the examples above, `folie`’s translation has more than one sense and therefore is not a member of any of the cases. `provision` has two translation polysemous translations and therefore belongs to case 2. `tr sor` has a monosemous translation and also comes with a French cue (`ressources`) and a semantic field (`comm` meaning commercial), and therefore belongs to cases 2, 3 and 4.

The figures for combinations of the above cases found in the bilingual dictionaries are the following:

---

[1] In this work we try to assign a single sense to the translations.

translation not in WordNet	4,081	24%
unique translation, n senses	4,761	28%
any combination of cases 1,2,3,4	8,075	48%
total	16,917	100%

Table 1

The figures mean that, from all the senses of French nouns, we can disambiguate at most 48% of them. The coverage of WordNet is not very impressive, only 76% of the English nouns in the bilingual dictionary. This is caused by several problems that will be dealt with below.

The bilingual subentries that provide disambiguation information have the distribution shown below. Some subentries belong at the same time to more than one case.

case 1; 1 sense	5,039	30%
case 2; more than one translation	630	4%
case 3; cue in French	2,954	17%
case 4; semantic field	1,067	6%

Table 2

Those that have a monosemous unique translation can be directly linked. Besides we still have not experimented with the use of semantic fields. Therefore, the algorithm will focus on bilingual subentries with multiple translations and/or cues in French.

2.2 Treatment of complex translations and cues

In the previous paragraph, it was said that 24% of the translations were not found in WordNet. A quick look at some of the translations revealed that the failure was sometimes caused by the translation being in a plural form, being composed by a whole noun phrase, brackets, etc. The same situation was observed in the cues, which were often composed by a phrase or a list of phrases. We call these translations and cues *complex*. Some examples of complex translations and cues follow:

```
batterie 2: n.f. (mus.) drums
e’poux 2: n.m. the married couple
escale 2: n.f. (port) port of call
microplaquette 1: n.f. (micro) chip
remonte’e 2: n.f. (d’eau, de prix) rise
```

The treatment for the translations and cues that could not be found directly in WordNet or the bilingual dictionary respectively was done in two steps. First, a morphological analysis was performed, and if it was not successful, combinations of the component words were tried.

A) morphological analysis: For English we use the morphological analyser provided by WordNet. In the case of French, a naive morphological analysis is tried (valid for nouns only), checking the resulting potential lemmas against the bilingual dictionary itself. For instance, morphological lookup for the translation for `batterie 2` would yield `drum`.

B) complex phrases: when the translation or cue is composed by more than one word, several combinations of the component words are tried. The longest combination of words that is successfully looked-up is returned. If no combination is succesful, then all the component words that are correct nouns (according to WordNet for English, and the bilingual dictionary for French) are returned. For the translation of `e'poux 2` this procedure would return `married couple`, which is correctly found in WordNet. In another example, `port of call` would yield both `port` and `call`. The same applies for cues: the processing of the cue `d'eau, de prix` would output both `eau` and `prix`. Brackets are also taken into account, but in this case the words inside brackets would never be returned on their own, only as components of a compound noun.

A sample of 50 complex translations was evaluated, to see the reliability of the method proposed. In 21% of the results, the single correct translation was proposed. The most significant part of the translation was captured in 67% of the cases, and only 12% of the proposed translations were wrong.

After processing the English translations, it was found that the coverage of WordNet increased from 76% to 95%, leaving only 891 subentries that could not be processed. This means that the figures for all cases in tables 1 and 2 change, as shown in tables 1' and 2'.

translation not in WordNet	891	5%
unique translation, n senses	6,440	38%
any combination of cases 1,2,3,4	9,586	57%
total	16,917	100%

Table 1'

case 1; 1 sense	5,119	30%
case 2; more than one translation	958	6%
case 3; cue in French	3,702	22%
case 4; semantic field	1,365	8%

Table 2'

2.3 The disambiguation procedure

In the core of the disambiguation procedure we use conceptual density as described in [Agirre & Rigau, 95], [Rigau 94] and [Agirre et al. 94]. Conceptual Density provides a basis for determining relatedness among words, taking as reference a structured hierarchical net which in this case is WordNet. For instance, in figure 1 we have a word W with four senses. Each sense belongs to a subtree in the hierarchical net. The dots in the subtrees represent the senses of either the word to be disambiguated (W) or the words in the context. Semantic Density will yield the highest density for the subtree containing more senses of those, relative to the total amount of senses in the subtree.

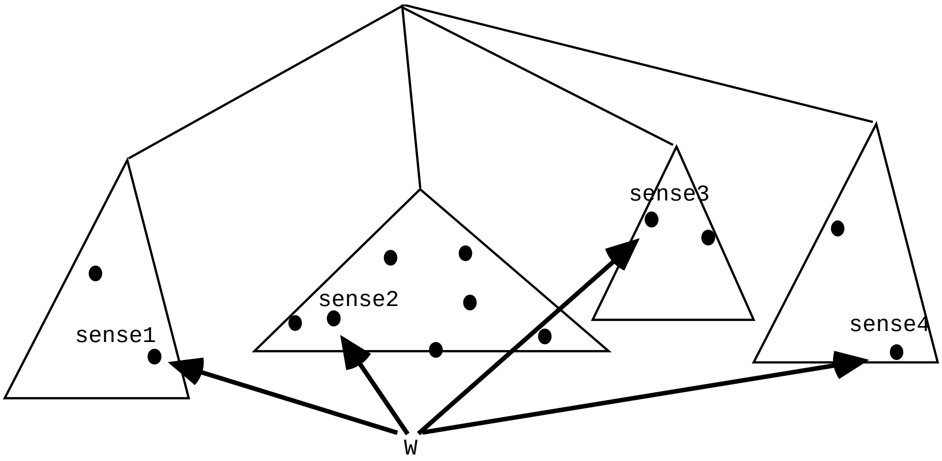

Figure 1: senses of a word in WordNet

The relatedness of a certain word-sense to the words in the context allows us to select that sense over the others. Following with the example in figure 1, sense2 would be chosen for W, because it belongs to the subtree with highest Semantic Density. In some cases more than one sense of the word to be disambiguated will belong to the selected subtree. In that case multiple senses are returned.

The context words are provided by the cue words in French and multiple translations. Cue words are in French, and therefore need to be translated into English, which is done using the bilingual dictionary.

In order to evaluate the contribution of each kind of contextual information separately, two experiments where performed on two sets of subentries: a set comprising French cues with a single translation word, and a set containing more than one translation but without any French cue.

2.4 Estimate the contribution of French cues

French cues are looked up in the bilingual dictionary, and all the English translations of the cue are input to the algorithm alongside the English translation. These English words will provide the necessary contextual information for the disambiguation of the translation.

A set of experiments was performed to evaluate the expected precision when disambiguating subentries that had a single English translation and a French cue. For this purpose, 59 French subentries fulfilling the given condition were selected at random

The precision and coverage are shown in the second line of the table below. The precision is considerably higher than random guessing[2]. The error rate was deemed too high, specially for some of the potential applications. In order to reduce the error rate several heuristics were tried. Declining to disambiguate translations with more than 5 senses was the most successful. As the third line of the following table shows, precision

[2] The figure for random guessig takes into account all noun entries. It was obtained analytically using the polysemy figures for all translations.

raised at the cost of the coverage.

	precision	coverage
random guessing	44.8%	-
original results	67.4%	72.9%
heuristic	83.3%	50.8%

Table 3

2.5 Estimate contribution of several translations

In this experiment 30 subentries that had more than one English translation were selected at random. The disambiguation algorithm was fed with the set of translation words and produced a set of WordNet synsets. The results, with and without applying the heuristic, are the following:

	precision	coverage
random guessing	44.8%	-
original results	89.3%	93.3%
heuristic	90.9%	73.3%

Table 4

Performance for this subset of the definitions is considerably better than for French cues. The heuristic does not yield significant improvement in precision, and the original results are preferred.

2.6 Overall results

Table 5 summarises the overall results. The algorithm was run over all the subentries, except those containing semantic fields. This means that in the best case, 8,221[3] subentries (53% of the total 15,552) could be linked. For a given subentry, whether it was monosemous or not was checked first. If not, disambiguation using multiple translations was tried, and last, cues in French were used. Monosemous translations account for most of the links made. The low coverage when disambiguating with French cues accounts for most of the failures to make links.

no result	8,311	53%
result obtained	7,241	47%
case 1; 1 sense	5,119	33%
case 2; >1 trans	723	5%
case 3; cue	1,399	9%
total	15,552	100%

Table 5

The links made, as calculated in the previous experiments, are highly reliable. The confidence for monosemous links (case 1) would be 100% if it not were because of complex translations, for which 88% of precision can be expected. For case 2, 93% of correct answers can be expected which descends to 83% for case 3 subentries.

[3] Calculated from tables 1' and 2', substracting the number of semantic fields from the overall combination of cases 1,2,3 and 4.

Overall coverage of this method will hopefully improve when semantic fields are taken into account.

3. MERGING LEXICAL KNOWLEDGE RESOURCES

Four experiments have been performed exploiting simple properties to attach Spanish nouns from the Spanish/English-English/Spanish bilingual dictionary to noun synsets in WordNet 1.5.

The nominal part of WordNet 1.5 has 60557 synsets and 87642 English nouns (76127 monosemous). The Spanish/English bilingual dictionary contains 12370 Spanish nouns and 11467 English nouns in 19443 connections among them. On the other hand, the English/Spanish bilingual dictionary is less informative than the other one containing only 10739 English nouns, 10549 Spanish nouns in 16324 connections.

Merging both dictionaries a list of equivalence pairs of nouns have been obtained. The combined dictionary contains 15848 English nouns, 14880 Spanish nouns and 28131 connections.

For instance, for the word "masa" in Spanish the following list of equivalence pairs can be obtained:

```
----------------------- English/Spanish
bulk masa
dough masa
mass masa
----------------------- Spanish/English
cake masa
crowd_of_people masa
dough masa
ground masa
mass masa
mortar masa
volume masa
```

From the combined dictionary, there are only 12665 English nouns placed in WordNet 1.5 which represents 19383 synsets. That is, the maximum coverage we can expect of WordNet1.5 using both bilingual Spanish/English dictionaries is 32%. In the next table the summarised amount of data is shown.

	English nouns	Spanish nouns	synsets	connections
WordNet1.5	87,642	-	60,557	107,424
Spanish/English	11,467	12,370	-	19,443
English/Spanish	10,739	10,549	-	16,324
Merged Bilingual	15,848	14,880	-	28,131
Maximum Coverage of WordNet of bilingual	12,665 14% 80%	13,208 - 90%	19,383 32% -	24,613 - 87%

Table 6

The connection of Spanish nouns to Synsets in WordNet 1.5 has been performed in the following cases:

1) Those Spanish nouns translations of monosemous English nouns (one sense in WordNet). Considering for instance that the noun abduction has only one sense in WordNet1.5[4] :

Synonyms/Hypernyms (Ordered by Frequency) of noun abduction
1 sense of abduction

Sense 1
<abduction>
=> <capture, seizure>
=> <felony>
=> <crime, law-breaking>
=> <evildoing, transgression>
=> <wrongdoing, misconduct>
=> <activity>
=> <act, human action, human activity>

and there are two possible translations for abduction for Spanish

secuestro <--> abduction
rapto <--> abduction

the following attachment has been produced:

<abduction> <--> <secuestro, rapto>

Only 6616 English nouns from the equivalence pairs list are monosemous (42% of the total English nouns). Thus, this simple approach has produced 9057 connections among 7636 Spanish nouns and 5963 synsets of WordNet1.5 with a very high degree of confidence. The polysemous degree in this case is 1.19 synsets per Spanish noun with 1.52 Spanish nouns per synset. Next table shows the results following this process.

[4] In the following examples, brackets are used indicating synsets (concepts) and => means hyponym-of.

	English nouns	Spanish nouns	synsets	connec.	Poly.	Syn.
WordNet	87,642	-	60,557	107,424	1.2	1.8
Bilingual	15,848	14,880	-	28,131		
Maximum Coverage	12,665	13,208	19,383	24,613	1.9	1.3
Case 1 of WordNet of Bilingual of Maximum of total	6,616 8% 42% 52% 58%	**7,636** - 51% 58% 63%	5,963 10% - 30% 37%	9,057 - - 37% 37%	1.2	1.5
Total	11,470	12,039	15,897	24,535		

Table 7

2) Those Spanish nouns with only one translation (although, the translation could be polysemous). Consider for instance the only translation found into the merged dictionary for the Spanish noun *anfibio* :

amphibian <--> anfibio

This process has produced three possible connections for the English WordNet1.5 amphibian:

<amphibian, amphibious vehicle> <--> <anfibio>
<amphibian, amphibious aircraft> <--> <anfibio>
<amphibian> <--> <anfibio>
=> <vertebrate, craniate>

There are 8524 Spanish nouns with only one translation. These Spanish nouns are equivalence candidates of 7507 English nouns but only 6066 of these are present in WordNet1.5. Thus, this approach has generated 14164 connections among 7000 Spanish nouns and 10674 synsets. The polysemous ratio is 2.02 synsets per Spanish noun and there are 1.33 Spanish word per synset. In the following table the results for this approach are shown.

	English nouns	Spanish nouns	synsets	connec.	Poly.	Syn.
WordNet	87,642	-	60,557	107,424	1.2	1.8
Bilingual	15,848	14,880	-	28,131		
Maximum Coverage	12,665	13,208	19,383	24,613	1.9	1.3
Case 2 of WordNet of Bilingual of Maximum of total	6,066 7% 38% 48% 53%	7,000 - 47% 53% 58%	**10,674** 18% - 55% 67%	**14,164** - - 58% 58%	2.0	1.3
Total	11,470	12,039	15,897	24,535		

Table 8

3) Those English nouns (although, the translation could be polysemous) with only one translation. Consider the unique translation of banishment for the nominal part of the bilingual dictionaries:

banishment <--> destierro

Thus, the Spanish noun *destierro* has been attached to both synsets of banishment in WordNet:

<banishment, ostracism> <--> <destierro>
=> <exclusion>
=> <situation, state of affairs>
=> <state>

<banishment, proscription> <--> <destierro>
=> <rejection>
=> <act, human action, human activity>

There are 10285 English nouns with only one translation (out of 7383 are present in WordNet). These English nouns are equivalence translations of 8556 Spanish nouns. In this case, 11089 connections have been produced among 6470 Spanish nouns and 10223 synsets. Thus, the polysemous ratio is 1.71 synsets per Spanish noun with 1.08 Spanish noun per synset. In next table this data is summarized.

	English nouns	Spanish nouns	synsets	connec.	Poly.	Syn.
WordNet	87,642	-	60,557	107,424	1.2	1.8
Bilingual	15,848	14,880	-	28,131		
Maximum Coverage	12,665	13,208	19,383	24,613	1.9	1.3
Case 3	**7,383**	6,470	10,223	11,089	1.7	1.1
of WordNet	8%	-	17%	-		
of Bilingual	47%	44%	-	-		
of Maximum	58%	49%	53%	45%		
of total	64%	54%	64%	45%		
Total	11,470	12,039	15,897	24,535		

Table 9

4) Those synsets with several English nouns with the same translation. Consider the following translations for the word *error* in the merged bilingual dictionary:

error <--> error
mistake <--> error

then this process can generate the following attachment:

<mistake, error, fault> <--> <error>
=> <failure>
=> <nonaccomplishment, nonachievement>
=> <act, human action, human activity>

<error, mistake> <--> <error>
=> <misstatement>
=> <statement>
=> <message, content, subject matter, substance>
=> <communication>
=> <social relation>
=> <relation>
=> <abstraction>

In this case, 3164 connections among 2261 Spanish nouns and 2195 synsets have been found. That means a polysemous ratio of 1.40 synsets per Spanish noun and 1.44 Spanish nouns per synset. The next table summarises the last approach.

	English nouns	Spanish nouns	synsets	connec.	Poly.	Syn.
WordNet	87,642	-	60,557	107,424	1.2	1.8
Bilingual	15,848	14,880	-	28,131		
Maximum Coverage	12,665	13,208	19,383	24,613	1.9	1.3
Case 4	2,092	2,261	2,195	3,164	1.4	1.4
of WordNet	2%	-	4%	-		
of Bilingual	13%	15%	-	-		
of Maximum	17%	17%	11%	13%		
of total	18%	19%	14%	13%		
Total	11,470	12,039	15,897	24,535		

Table 10

Merging all the connections we have obtained a micro-Spanish WordNet (with errors). The resulting data has 24535 connections among 12039 Spanish nouns and 15897 synsets of WordNet1.5. That is to say, a polysemous ratio of 2.03 synsets per Spanish noun with 1.54 synonymy degree. The next table shows the overall data:

	English nouns	Spanish nouns	synsets	connec.	Poly.	Syn.
WordNet	87,642		60,557	107,424	1.2	1.8
Bilingual	15,848	14,880		28,131		
Maximum Coverage	12,665	13,208	19,383	24,613	1.9	1.3
Case 1	6,616	**7,636**	5,963	9,057	1.2	1.5
Case 2	6,066	7,000	**10,674**	**14,164**	2.0	1.3
Case 3	**7,383**	6,470	10,223	11,089	1.7	1.1
Case 4	2,092	2,261	2,195	3,164	1.4	1.4
Total	11,470	12,039	15,897	24,535	2.0	1.5
of WordNet	13%	-	26%	-		
of Bilingual	72%	80%	-	-		
of Maximum	90%	91%	82%	100%		

Table 11

We have tested manually one hundred connections. 78 out of 100 were correct. Obviously, the most productive cases are the cases that introduce more errors.

4. CONSIDERATIONS

This paper shows that disambiguating bilingual nominal entries, and therefore linking bilingual dictionaries to WordNet is a feasible task. The complementary approaches presented here, Semantic Density on entry information and merging taking profit of dictionary structure, both attain high levels of precision on their own. The combination of both techniques, alongside using the semantic fields left aside by the first approach, should yield better precision and a raise in coverage. For instance, the first approach focuses on the information in the French/English direction of the dictionary, without using the reverse direction or exploiting the structure of the dictionary as in the second approach. The second approach, on the other hand, could take profit from both the information in each entry and the inferential capability of Semantic Density.

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Combining Unsupervised Lexical Knowledge Methods for Word Sense Disambiguation *

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Abstract

This paper presents a method to combine a set of unsupervised algorithms that can accurately disambiguate word senses in a large, completely untagged corpus. Although most of the techniques for word sense resolution have been presented as stand-alone, it is our belief that full-fledged lexical ambiguity resolution should combine several information sources and techniques. The set of techniques have been applied in a combined way to disambiguate the genus terms of two machine-readable dictionaries (MRD), enabling us to construct complete taxonomies for Spanish and French. Tested accuracy is above 80% overall and 95% for two-way ambiguous genus terms, showing that taxonomy building is not limited to structured dictionaries such as LDOCE.

1 Introduction

While in English the "lexical bottleneck" problem (Briscoe, 1991) seems to be softened (e.g. WordNet (Miller, 1990), Alvey Lexicon (Grover et al., 1993), COMLEX (Grishman et al., 1994), etc.) there are no available wide range lexicons for natural language processing (NLP) for other languages. Manual construction of lexicons is the most reliable technique for obtaining structured lexicons but is costly and highly time-consuming. This is the reason for many researchers having focused on the massive acquisition of lexical knowledge and semantic information from pre-existing structured lexical resources as automatically as possible.

As dictionaries are special texts whose subject matter is a language (or a pair of languages in the case of bilingual dictionaries) they provide a wide range of information about words by giving definitions of senses of words, and, doing that, supplying knowledge not just about language, but about the world itself.

One of the most important relation to be extracted from machine-readable dictionaries (MRD) is the hyponym/hypernym relation among dictionary senses (e.g. (Amsler, 1981), (Vossen and Serail, 1990)) not only because of its own importance as the backbone of taxonomies, but also because this relation acts as the support of main inheritance mechanisms helping, thus, the acquisition of other relations and semantic features (Cohen and Loiselle, 1988), providing formal structure and avoiding redundancy in the lexicon (Briscoe et al., 1990). For instance, following the natural chain of dictionary senses described in the *Diccionario General Ilustrado de la Lengua Española* (DGILE, 1987) we can discover that a *bonsai* is a cultivated plant or bush.

bonsai_1_2 *planta y arbusto así cultivado.*
(bonsai, plant and bush cultivated in that way)

The hyponym/hypernym relation appears between the entry word (e.g. *bonsai*) and the genus term, or the core of the phrase (e.g. *planta* and *arbusto*). Thus, usually a dictionary definition is written to employ a genus term combined with differentia which distinguishes the word being defined from other words with the same genus term[1].

As lexical ambiguity pervades language in texts, the words used in dictionary are themselves lexically ambiguous. Thus, when constructing complete disambiguated taxonomies, the correct dictionary sense of the genus term must be selected in each dictionary

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[1]For other kind of definition patterns not based on genus, a genus-like term was added after studying those patterns.

	DGILE		LPPL	
	overall	nouns	overall	nouns
headwords	93,484	53,799	15,953	10,506
senses	168,779	93,275	22,899	13,740
total number of words	1,227,380	903,163	97,778	66,323
average length of definition	7.26	9.68	3.27	3.82

Table 1: Dictionary Data

definition, performing what is usually called Word Sense Disambiguation (WSD)[2]. In the previous example *planta* has thirteen senses and *arbusto* only one.

Although a large set of dictionaries have been exploited as lexical resources, the most widely used monolingual MRD for NLP is LDOCE which was designed for learners of English. It is clear that different dictionaries do not contain the same explicit information. The information placed in LDOCE has allowed to extract other implicit information easily, e.g. taxonomies (Bruce et al., 1992). Does it mean that only highly structured dictionaries like LDOCE are suitable to be exploited to provide lexical resources for NLP systems?

We explored this question probing two disparate dictionaries: *Diccionario General Ilustrado de la Lengua Española* (DGILE, 1987) for Spanish, and *Le Plus Petit Larousse* (LPPL, 1980) for French. Both are substantially poorer in coded information than LDOCE (LDOCE, 1987)[3]. These dictionaries are very different in number of headwords, polysemy degree, size and length of definitions (c.f. table 1). While DGILE is a good example of a large sized dictionary, LPPL shows to what extent the smallest dictionary is useful.

Even if most of the techniques for WSD are presented as stand-alone, it is our belief, following the ideas of (McRoy, 1992), that full-fledged lexical ambiguity resolution should combine several information sources and techniques. This work does not address all the heuristics cited in her paper, but profits from techniques that were at hand, without any claim of them being complete. In fact we use unsupervised techniques, i.e. those that do not require hand-coding of any kind, that draw knowledge from a variety of sources – the source dictionaries, bilingual dictionaries and WordNet – in diverse ways.

[2]Called also Lexical Ambiguity Resolution, Word Sense Discrimination, Word Sense Selection or Word Sense Identification.

[3]In LDOCE, dictionary senses are explicitly ordered by frequency, 86% dictionary senses have semantic codes and 44% of dictionary senses have pragmatic codes.

This paper tries to proof that using an appropriate method to combine those heuristics we can disambiguate the genus terms with reasonable precision, and thus construct complete taxonomies from any conventional dictionary in any language.

This paper is organized as follows. After this short introduction, section 2 shows the methods we have applied. Section 3 describes the test sets and shows the results. Section 4 explains the construction of the lexical knowledge resources used. Section 5 discusses previous work, and finally, section 6 faces some conclusions and comments on future work.

2 Heuristics for Genus Sense Disambiguation

As the methods described in this paper have been developed for being applied in a combined way, each one must be seen as a container of some part of the knowledge (or heuristic) needed to disambiguate the correct hypernym sense. Not all the heuristics are suitable to be applied to all definitions. For combining the heuristics, each heuristic assigns each candidate hypernym sense a normalized weight, i.e. a real number ranging from 0 to 1 (after a scaling process, where maximum score is assigned 1, c.f. section 2.9). The heuristics applied range from the simplest (e.g. heuristic 1, 2, 3 and 4) to the most informed ones (e.g. heuristics 5, 6, 7 and 8), and use information present in the entries under study (e.g. heuristics 1, 2, 3 and 4) or extracted from the whole dictionary as a unique lexical knowledge resource (e.g. heuristics 5 and 6) or combining lexical knowledge from several heterogeneous lexical resources (e.g. heuristic 7 and 8).

2.1 Heuristic 1: Monosemous Genus Term

This heuristic is applied when the genus term is monosemous. As there is only one hypernym sense candidate, the hyponym sense is attached to it. Only 12% of noun dictionary senses have monosemous genus terms in DGILE, whereas the smaller LPPL reaches 40%.

2.2 Heuristic 2: Entry Sense Ordering

This heuristic assumes that senses are ordered in an entry by frequency of usage. That is, the most used and important senses are placed in the entry before less frequent or less important ones. This heuristic provides the maximum score to the first sense of the hypernym candidates and decreasing scores to the others.

2.3 Heuristic 3: Explicit Semantic Domain

This heuristic assigns the maximum score to the hypernym sense which has the same semantic domain tag as the hyponym. This heuristic is of limited application: LPPL lacks semantic tags, and less than 10% of the definitions in DGILE are marked with one of the 96 different semantic domain tags (e.g. *med.* for medicine, or *der.* for law, etc.).

2.4 Heuristic 4: Word Matching

This heuristic trusts that related concepts will be expressed using the same content words. Given two definitions – that of the hyponym and that of one candidate hypernym – this heuristic computes the total amount of content words shared (including headwords). Due to the morphological productivity of Spanish and French, we have considered different variants of this heuristic. For LPPL the match among lemmas proved most useful, while DGILE yielded better results when matching the first four characters of words.

2.5 Heuristic 5: Simple Cooccurrence

This heuristic uses cooccurrence data collected from the whole dictionary (see section 4.1 for more details). Thus, given a hyponym definition (O) and a set of candidate hypernym definitions, this method selects the candidate hypernym definition (E) which returns the maximum score given by formula (1):

$$SC(O,E) = \sum_{w_i \in O \wedge w_j \in E} cw(w_i, w_j) \qquad (1)$$

The cooccurrence weight (cw) between two words can be given by Cooccurrence Frequency, Mutual Information (Church and Hanks, 1990) or Association Ratio (Resnik, 1992). We tested them using different context window sizes. Best results were obtained in both dictionaries using the Association Ratio. In DGILE window size 7 proved the most suitable, whereas in LPPL whole definitions were used.

2.6 Heuristic 6: Cooccurrence Vectors

This heuristic is based on the method presented in (Wilks et al., 1993) which also uses cooccurrence data collected from the whole dictionary (c.f. section 4.1). Given a hyponym definition (O) and a set of candidate hypernym definitions, this method selects the candidate hypernym (E) which returns the maximum score following formula (2):

$$CV(O,E) = sim(V_O, V_E) \qquad (2)$$

The similarity (sim) between two definitions can be measured by the dot product, the cosine function or the Euclidean distance between two vectors (V_O and V_E) which represent the contexts of the words presented in the respective definitions following formula (3):

$$V_{Def} = \sum_{w_i \in Def} civ(w_i) \qquad (3)$$

The vector for a definition (V_{Def}) is computed adding the cooccurrence information vectors of the words in the definition ($civ(w_i)$). The cooccurrence information vector for a word is collected from the whole dictionary using Cooccurrence Frequency, Mutual Information or Association Ratio. The best combination for each dictionary vary: whereas the dot product, Association Ratio, and window size 7 proved best for DGILE, the cosine, Mutual Information and whole definitions were preferred for LPPL.

2.7 Heuristic 7: Semantic Vectors

Because both LPPL and DGILE are poorly semantically coded we decided to enrich the dictionary assigning automatically a semantic tag to each dictionary sense (see section 4.2 for more details). Instead of assigning only one tag we can attach to each dictionary sense a vector with weights for each of the 25 semantic tags we considered (which correspond to the 25 lexicographer files of WordNet (Miller, 1990)). In this case, given an hyponym (O) and a set of possible hypernyms we select the candidate hypernym (E) which yields maximum similarity among semantic vectors:

$$SV(O,E) = sim(V_O, V_E) \qquad (4)$$

where sim can be the dot product, cosine or Euclidean Distance, as before. Each dictionary sense has been semantically tagged with a vector of semantic weights following formula (5).

$$V_{Def} = \sum_{w_i \in Def} swv(w_i) \qquad (5)$$

The salient word vector (swv) for a word contains a saliency weight (Yarowsky, 1992) for each of the 25 semantic tags of WordNet. Again, the best method differs from one dictionary to the other: each one prefers the method used in the previous section.

2.8 Heuristic 8: Conceptual Distance

Conceptual distance provides a basis for determining closeness in meaning among words, taking as reference a structured hierarchical net. Conceptual distance between two concepts is essentially the length of the shortest path that connects the concepts in the hierarchy. In order to apply conceptual distance, WordNet was chosen as the hierarchical knowledge base, and bilingual dictionaries were used to link Spanish and French words to the English concepts.

Given a hyponym definition (O) and a set of candidate hypernym definitions, this heuristic chooses the hypernym definition (E) which is closest according to the following formula:

$$CD(O, E) = dist(headword_O, genus_E) \quad (6)$$

That is, Conceptual Distance is measured between the headword of the hyponym definition and the genus of the candidate hypernym definitions using formula (7), c.f. (Agirre et al., 1994). To compute the distance between any two words (w_1,w_2), all the corresponding concepts in WordNet (c_{1_i}, c_{2_j}) are searched via a bilingual dictionary, and the minimum of the summatory for each concept in the path between each possible combination of c_{1_i} and c_{2_j} is returned, as shown below:

$$dist(w_1, w_2) = \min_{\substack{c_{1_i} \in w_1 \\ c_{2_j} \in w_2}} \sum_{\substack{c_k \in \\ path(c_{1_i}, c_{2_j})}} \frac{1}{depth(c_k)} \quad (7)$$

Formulas (6) and (7) proved the most suitable of several other possibilities for this task, including those which included full definitions in (6) or those using other Conceptual Distance formulas, c.f. (Agirre and Rigau, 1996).

2.9 Combining the heuristics: Summing

As outlined in the beginning of this section, the way to combine all the heuristics in one single decision is simple. The weights each heuristic assigns to the rivaling senses of one genus are normalized to the interval between 1 (best weight) and 0. Formula (8) shows the normalized value a given heuristic will give to sense E of the genus, according to the weight assigned to the heuristic to sense E and the maximum weight of all the sense of the genus E_i.

$$vote(O, E) = \frac{weight(O, E)}{\max_{E_i}(weigth(O, E_i))} \quad (8)$$

The values thus collected from each heuristic, are added up for each competing sense. The order in which the heuristics are applied has no relevance at all.

	DGILE	LPPL
Test Sampling	391	115
Correct Genus Selected	382 (98%)	111 (97%)
Monosemous	61 (16%)	40 (36%)
Senses per genus	2.75	2.29
idem (polysemous only)	3.64	3.02
Correct senses per genus	1.38	1.05
idem (polysemous only)	1.51	1.06

Table 2: Test Sets

3 Evaluation

3.1 Test Set

In order to test the performance of each heuristic and their combination, we selected two test sets at random (one per dictionary): 391 noun senses for DGILE and 115 noun senses for LPPL, which give confidence rates of 95% and 91% respectively. From these samples, we retained only those for which the automatic selection process selected the correct genus (more than 97% in both dictionaries). Both test sets were disambiguated by hand. Where necessary multiple correct senses were allowed in both dictionaries. Table 2 shows the data for the test sets.

3.2 Results

Table 3 summarizes the results for polysemous genus.

In general, the results obtained for each heuristic seem to be poor, but always over the random choice baseline (also shown in tables 3 and 4). The best heuristics according to the recall in both dictionaries is the sense ordering heuristic (2). For the rest, the difference in size of the dictionaries could explain the reason why cooccurrence-based heuristics (5 and 6) are the best for DGILE, and the worst for LPPL. Semantic distance gives the best precision for LPPL, but chooses an average of 1.25 senses for each genus.

With the combination of the heuristics (Sum) we obtained an improvement over sense ordering (heuristic 2) of 9% (from 70% to 79%) in DGILE, and of 7% (from 66% to 73%) in LPPL, maintaining in both cases a coverage of 100%. Including monosemous genus in the results (c.f. table 4), the sum is able to correctly disambiguate 83% of the genus in DGILE (8% improvement over sense ordering) and 82% of the genus in LPPL (4% improvement). Note that we are adding the results of eight different heuristics with eight different performances, improving the individual performance of each one.

In order to test the contribution of each heuristic to the total knowledge, we tested the sum of all the heuristics, eliminating one of them in turn. The results are provided in table 5.

LPPL	random	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Sum
recall	36%	-	66%	-	8%	11%	22%	11%	50%	73%
precision	36%	-	66%	-	66%	44%	61%	57%	76%	73%
coverage	100%	-	100%	-	12%	25%	36%	19%	66%	100%
DGILE										
recall	30%	-	70%	1%	44%	57%	60%	57%	47%	79%
precision	30%	-	70%	100%	72%	57%	60%	58%	49%	79%
coverage	100%	-	100%	1%	61%	100%	100%	99%	95%	100%

Table 3: Results for polysemous genus.

LPPL	random	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Sum
recall	59%	35%	78%	-	40%	42%	50%	42%	68%	82%
precision	59%	100%	78%	-	93%	82%	84%	88%	87%	82%
coverage	100%	35%	100%	-	43%	51%	59%	48%	78%	100%
DGILE										
recall	41%	16%	75%	2%	41%	59%	63%	59%	48%	83%
precision	41%	100%	75%	100%	79%	65%	66%	63%	57%	83%
coverage	100%	16%	100%	2%	56%	95%	97%	94%	89%	100%

Table 4: Overall results.

LPPL	Sum	-(1)	-(2)	-(3)	-(4)	-(5)	-(6)	-(7)	-(8)
recall	82%	73%	74%	-	73%	76%	77%	77%	78%
precision	82%	73%	75%	-	73%	76%	77%	77%	78%
coverage	100%	100%	99%	-	100%	100%	100%	100%	100%
DGILE									
recall	83%	79%	72%	81%	81%	81%	81%	81%	77%
precision	83%	79%	72%	82%	81%	81%	81%	81%	77%
coverage	100%	100%	100%	98%	100%	100%	100%	100%	100%

Table 5: Knowledge provided by each heuristic (overall results).

(Gale et al., 1993) estimate that any sense-identification system that does not give the correct sense of polysemous words more than 75% of the time would not be worth serious consideration. As table 5 shows this is not the case in our system. For instance, in DGILE heuristic 8 has the worst performance (see table 4, precision 57%), but it has the second larger contribution (see table 5, precision decreases from 83% to 77%). That is, even those heuristics with poor performance can contribute with knowledge that other heuristics do not provide.

3.3 Evaluation

The difference in performance between the two dictionaries show that quality and size of resources is a key issue. Apparently the task of disambiguating LPPL seems easier: less polysemy, more monosemous genus and high precision of the sense ordering heuristic. However, the heuristics that depend only on the size of the data (5, 6) perform poorly on LPPL, while they are powerful methods for DGILE.

The results show that the combination of heuristics is useful, even if the performance of some of the heuristics is low. The combination performs better than isolated heuristics, and allows to disambiguate all the genus of the test set with a success rate of 83% in DGILE and 82% in LPPL.

All the heuristics except heuristic 3 can readily be applied to any other dictionary. Minimal parameter adjustment (window size, cooccurrence weigth formula and vector similarity function) should be done to fit the characteristics of the dictionary, but according to our results it does not alter significantly the results after combining the heuristics.

4 Derived Lexical Knowledge Resources

4.1 Cooccurrence Data

Following (Wilks et al., 1993) two words cooccur if they appear in the same definition (word order in definitions are not taken into account). For instance, for DGILE, a lexicon of 300,062 cooccurrence pairs among 40,193 word forms was derived (stop words were not taken into account). Table 6 shows the first eleven words out of the 360 which cooccur with *vino* (wine) ordered by Association Ratio. From left to right, Association Ratio and number of occurrences.

The lexicon (or machine-tractable dictionary,

AR	#oc.	
11.1655	15	*tinto* (red)
10.0162	23	*beber* (to drink)
9.6627	14	*mosto* (must)
8.6633	9	*jerez* (sherry)
8.1051	9	*cubas* (cask, barrel)
8.0551	16	*licor* (liquor)
7.2127	17	*bebida* (drink)
6.9338	12	*uva* (grape)
6.8436	9	*trago* (drink, swig)
6.6221	12	*sabor* (taste)
6.4506	15	*pan* (bread)

Table 6: Example of association ratio for *vino* (wine).

MTD) thus produced from the dictionary is used by heuristics 5 and 6.

4.2 Multilingual Data

Heuristics 7 and 8 need external knowledge, not present in the dictionaries themselves. This knowledge is composed of semantic field tags and hierarchical structures, and both were extracted from WordNet. In order to do this, the gap between our working languages and English was filled with two bilingual dictionaries. For this purpose, we derived a list of links for each word in Spanish and French as follows.

Firstly, each Spanish or French word was looked up in the bilingual dictionary, and its English translation was found. For each translation WordNet yielded its senses, in the form of WordNet concepts (synsets). The pair made of the original word and each of the concepts linked to it, was included in a file, thus producing a MTD with links between Spanish or French words and WordNet concepts. Obviously some of this links are not correct, as the translation in the bilingual dictionary may not necessarily be understood in its senses (as listed in WordNet). The heuristics using these MTDs are aware of this.

For instance when accessing the semantic fields for *vin* (French) we get a unique translation, wine, which has two senses in WordNet: `<wine,vino>` as a beverage, and `<wine, wine-coloured>` as a kind of color. In this example two links would be produced (*vin*, `<wine,vino>`) and (*vin*, `<wine, wine-coloured>`). This link allows us to get two possible semantic fields for *vin* (`noun.food`, file 13, and `noun.attribute`, file 7) and the whole structure of the hierarchy in WordNet for each of the concepts.

5 Comparison with Previous Work

Several approaches have been proposed for attaching the correct sense (from a set of prescribed ones) of a word in context. Some of them have been fully tested in real size texts (e.g. statistical methods (Yarowsky, 1992), (Yarowsky, 1994), (Miller and Teibel, 1991), knowledge based methods (Sussna, 1993), (Agirre and Rigau, 1996), or mixed methods (Richardson et al., 1994), (Resnik, 1995)). The performance of WSD is reaching a high stance, although usually only small sets of words with clear sense distinctions are selected for disambiguation (e.g. (Yarowsky, 1995) reports a success rate of 96% disambiguating twelve words with two clear sense distinctions each one).

This paper has presented a general technique for WSD which is a combination of statistical and knowledge based methods, and which has been applied to disambiguate all the genus terms in two dictionaries.

Although this latter task could be seen easier than general WSD[4], genus are usually frequent and general words with high ambiguity[5]. While the average of senses per noun in DGILE is 1.8 the average of senses per noun genus is 2.75 (1.30 and 2.29 respectively for LPPL). Furthermore, it is not possible to apply the powerful "one sense per discourse" property (Yarowsky, 1995) because there is no discourse in dictionaries.

WSD is a very difficult task even for humans[6], but semiautomatic techniques to disambiguate genus have been broadly used (Amsler, 1981) (Vossen and Serail, 1990) (Ageno et al., 1992) (Artola, 1993) and some attempts to do automatic genus disambiguation have been performed using the semantic codes of the dictionary (Bruce et al., 1992) or using cooccurrence data extracted from the dictionary itself (Wilks et al., 1993).

Selecting the correct sense for LDOCE genus terms, (Bruce et al., 1992) report a success rate of 80% (90% after hand coding of ten genus). This impressive rate is achieved using the intrinsic char-

[4]In contrast to other sense distinctions Dictionary word senses frequently differ in subtle distinctions (only some of which have to do with meaning (Gale et al., 1993)) producing a large set of closely related dictionary senses (Jacobs, 1991).

[5]However, in dictionary definitions the headword and the genus term have to be the same part of speech.

[6](Wilks et al., 1993) disambiguating 197 occurrences of the word bank in LDOCE say "was not an easy task, as some of the usages of bank did not seem to fit any of the definitions very well". Also (Miller et al., 1994) tagging semantically SemCor by hand, measure an error rate around 10% for polysemous words.

acteristics of LDOCE. Furthermore, using only the implicit information contained into the dictionary definitions of LDOCE (Cowie et al., 1992) report a success rate of 47% at a sense level. (Wilks et al., 1993) reports a success rate of 45% disambiguating the word bank (thirteen senses LDOCE) using a technique similar to heuristic 6. In our case, combining informed heuristics and without explicit semantic tags, the success rates are 83% and 82% overall, and 95% and 75% for two-way ambiguous genus (DGILE and LPPL data, respectively). Moreover, 93% and 92% of times the real solution is between the first and second proposed solution.

6 Conclusion and Future Work

The results show that computer aided construction of taxonomies using lexical resources is not limited to highly-structured dictionaries as LDOCE, but has been succesfully achieved with two very different dictionaries. All the heuristics used are unsupervised, in the sense that they do not need hand-codding of any kind, and the proposed method can be adapted to any dictionary with minimal parameter setting.

Nevertheless, quality and size of the lexical knowledge resources are important. As the results for LPPL show, small dictionaries with short definitions can not profit from raw corpus techniques (heuristics 5, 6), and consequently the improvement of precision over the random baseline or first-sense heuristic is lower than in DGILE.

We have also shown that such a simple technique as just summing is a useful way to combine knowledge from several unsupervised WSD methods, allowing to raise the performance of each one in isolation (coverage and/or precision). Furthermore, even those heuristics with apparently poor results provide knowledge to the final result not provided by the rest of heuristics. Thus, adding new heuristics with different methodologies and different knowledge (e.g. from corpora) as they become available will certainly improve the results.

Needless to say, several improvements can be done both in individual heuristic and also in the method to combine them. For instance, the cooccurrence heuristics have been applied quite indiscriminately, even in low frequency conditions. Significance tests or association coefficients could be used in order to discard low confidence decisions. Also, instead of just summing, more clever combinations can be tried, such as training classifiers which use the heuristics as predictor variables.

Although we used these techniques for genus disambiguation we expect similar results (or even better taken the "one sense per discourse" property and lexical knowledge acquired from corpora) for the WSD problem.

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KONTZEPTUEN ARTEKO ERLAZIO-IZAERAREN FORMALIZAZIOA ONTOLOGIAK ERABILIAZ: DENTSITATE KONTZEPTUALA

aplikazioak ezagutza-base lexikalen eraikuntzan, adiera-desanbiguazioan eta testu-zuzenketa automatikoan

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Informatikan Doktore titulua eskuratzeko aurkezturiko

TESI-TXOSTENA

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Eneko Agirre Bengoak **Kepa Sarasola Gabiola** eta **Arantza Diaz de Ilarrazaren** zuzendaritzapean egindako tesiaren txostena, Euskal Herriko Unibertsitatean Informatikan Doktore titulua eskuratzeko aurkeztua.

Donostia, 1998ko urria.

ESKER ONAK

Tesi-lan hau ez litzateke hemen egongo IXA taldea ezagutu izan ez banu.
Talde honen filosofia eta lanerako motibazioa kontagiosoa da oso.
Bereziki eskertu behar dut Kepa eta Arantzaren arreta, baita Koldorekin egindako elkar-lana ere.
Basamortuko lurralde beroetan Germanekin lan egitea ere erabakiorra izan da ikerkuntzarako trebatze bide luze honetan.

Batzuk lanean lagundu badute, beste askok tesitik aldentzea eragin dute, nire onerako.

tesiari denbora *kendu* diotenei:

guraso eta arreba; eibarko koadrila; alde-zaharreko pisuan alperkerira bultzatzen nindutenak; UEUko informatika saila; fakultateko parrandero kuadrila zabal eta nekagaitza, arratsaldero musean aritzeko kapaz ere diren horiek; asteroko palazale amorratuak; fosacomun eta bulegokalte jendetsu eta bizi haietan zeuden bekari zalapartariak; geroago IXA taldekoen artean metro karratu gutxi batzutan ere konzentratu genuena; bulegoko leihotik eguerdi aldera filtratzen den patata-tortila usaina; eta serioago, euskara-talde, intsumisio eta euskal preso politikoak (pankartagintza alaia dela!)

azken finean, ana, dena ez da lana, ez da?

AURKIBIDEA

IRUDIEN AURKIBIDEA

TAULEN AURKIBIDEA

HIZTEGIA

Abarkatze-faktore. Branching factor

Adimen Artifizial. Artificial Intelligence

Agerkidetza. Co-occurrence

Antzekotasun. Similarity

Arbaso. Ancestor

Benetako-hitz errore. Real-word error

Datu urrien arazo. Sparse data problem

Dentsitate Kontzeptual (DK). Conceptual Density

Distantzia Kontzeptual. Conceptual Distance

Doitasun. Precision

Dokumentuen berreskuratze. Document retrieval

Dokumentuen sailkapen. Document clustering

Elkarren Arteko Informazio (EAI). Mutual Information

Erabaki-zerrenda. Decision list

Eraginkortasun. Efficiency

Erlazio-izaera . Relatedness

Erlazio-izaera paradigmatiko. Paradigmatic Relatedness

Erlazio-izaera sintagmatiko. Syntagmatic Relatedness

Erlazionatutako. Related

Estaldura. Coverage

Ezagutza-base lexikal (EBL). Lexical Knowledge Base

Ez-hitz errore. Non-word error

Goi-ontologia. Top ontology

Hautapen-murrizpen. Selectional restriction

Hitz isolatuen zuzenketa. Isolated Word Correction

Hitzen adiera-desanbiguazio (HAD). Word Sense Disambiguation

Hiztegi elektroniko. Machine Readable Dictionary

Hiztegi ezagutza-base (HEB). Dictionary Knowledge Base

Hurbiltasun. Proximity, closeness

Informazioaren berreskuratze. Information Retrieval

Informazio-eduki. Information content

Karaktere-ezagutze optiko. Optical character recognition

Kategoria-etiketatzaile. Part of speech tagger

Lengoaia Naturalaren Prozesamendu (LNP). Natural Language Processing (NLP)

Leuntze. Smoothing

Log-sinesgarritasun. Log-likelihood

Markov-en eredu izkutu. Hidden Markov Model

Multzokatze. Clustering

Murrizpen-Gramatika (MG). Constraint Grammar

Nabaritasun. Relevance

Nabarmentasun. Saliency

Nahaste-multzo. Confusion-set

Ondorengo. Descendant

Sendotasun. Robustness

Testuingururik gabeko gramatika hedatu. Augmented Context-Free Gramars

Thesaurus. Thesaurus

Zati erlazioa. Part-of relation

LABURDURAK

AA. Agerkidetza arruntak

AB. Agerkidetza bektoreak

AR. *Association Ratio*

BM. Brown maiztasunak

DK. Dentsitate Kontzeptual

DM. Dokumentuko maiztasunak

EAI. Elkarren Arteko Informazio

EBL. Ezagutza-Base Lexikal

EZ. Definizioko hitzen ezkontzea

H1. Izen nagusien heuristikoa

H2. Hitz laburren heuristikoa

HAD. Hitzen Adiera-Desanbiguazio

HEB. Hiztegi Ezagutza-Base

LNP. Lengoaia Naturalaren Prozesamendu

LPPL. *Le Plus Petit Larousse*

MG. Murrizpen-gramatika

OFED. Oxford French/English Dictionary

OR. Adieren ordena

SB. Etiketa semantikoen bektoreak

TS. Testuingurua kontuan hartzen duen metodoa

WN. WordNet

I. Kapitulua

PROIEKTUAREN AURKEZPENA

I.A. Motibazioa

Gizakiok era naturalean erabakitzen dugu edozein gauza zein puntutaraino erlazionatuta dauden ala ez. Zer dago ardiarekin erlazionatuago, behia, bixigua ala irratia? Halako galderei erantzuteko arazorik ez dugu izaten. Ordenadoreek aldiz, sen onaren alderdi gehienekin gertatzen den bezala, ez daukate nondik heldu galdera horri. Ez dakite zer diren ardia, bixigu edo irratia, ezta beraien arteko erlazioak zeintzuk diren. Galdera horri erantzun ahal izanez gero aplikazio interesgarri askotara hedatu ahal izango dira ordenadoreak. Gu Lengoaia Naturalaren Prozesamenduan (LNP) zentratuko gara. Askoren ustez halako galderei erantzuteko ahalmena da prozesamendu semantikoaren giltza. Ahalmen horri erlazio-izaeraren neurri deitzen diogu, hau da, bi hitzen arteko erlazioak zer indar duen emango digun neurria. Neurri hau izenentzat batez ere definitu ohi da.

Erlazio-izaera formalizatzeko aukera ezberdinak aztertu izan dira literaturan. Lan batzuetan hitzen arteko erlazio-izaera landu izan da soilik, baina beste askok adierekin lan egiten dute. Lehenbizikoek, adibidez, *banku*-ren adiera ezberdinen artean ezin dute bereizi, baina bigarrenek *banku* eta *aulki* hertsiki erlazionatuta dauden ala ez galderari, "segun" erantzungo liokete: *banku* hori esertzekoa baldin bada orduan bai, baina eraikuntza bada, diruarekin zer ikusia duena, orduan ez daude hain hertsiki erlazionatuta. Hitzen arteko erlazio-izaera baino, ene ustez, adieren artekoaren formalizazioa interesgarriagoa da.

Formalizazioak oinarri duten baliabide lexikalaren arabera ere sailka daitezke:

- idatzizko testu multzoak diren corpusak erabiltzen dituztenak
- hiztegietako informazioa erabiltzen dutenak, bereziki hitzen definizioak

- ezagutza egituratua darabiltenak, hala nola, Hiztegi Ezagutza-Base (HEB), Ezagutza-Base Lexikal (EBL) eta ontologiak.

Hiru baliabide motak aztertu ondoren ezagutza egituratuan oinarritzea iruditu zaigu zentzuzkoena. Baliabide lexikal guztiek daukate informazio interesgarria, hein handi batean bata bestearen osagarria dena. Hala ere tradizio sendoena ontologian oinarritutako neurriena da, psikologia eta adimen artifizialeko lanetan errotua. Erabaki horretan EBL zabal bat, WordNet, eskura eduki ahal izateak lagundu digu, eta ezagutza-base horren gainean inplementatu dugu erlazio-izaeraren neurria. III.A atalean baliabide ezberdinetan oinarritutako neurriak aztertuko ditugu, eta III.D atalean ontologiatan oinarritutakoak hobesteko arrazoiak azaldu. Guk aurkezten dugun izenen arteko erlazio-izaeraren neurriari Dentsitate Kontzeptual (DK) deitzen diogu, eta ontologiako kontzeptuen arteko hierarkian oinarritzen da. Nahiz eta WordNet-eko ontologia erabiliaz inplementatu, kontzeptuen hierarkia eta erlazioak dituen edozein baliabide lexikaletan aplika daiteke.

Adieren arteko erlazio-izaeraren neurria aplikazio askotarako ezinbestekoa edo gutxienez lagungarria da, hala nola, egitura sintaktikoen desanbiguazioa, hitzen adiera desanbiguazioa, ontologien eraikuntza, hautapen-murrizpenen ikasketa, ontologia ezberdinen bat egitea, ontologien ebaluazioa, informazioaren berreskuratzea, dokumentuen berreskuratze eta sailkapena, kontzeptuen multzokatzea, testu-zuzenketa automatikoa, bai eta interpretazio semantiko orokorra ere.

Erlazio-izaera sarri azaltzen zaigu Hitzen Adiera-Desanbiguazioari (HAD) lotuta, eta aplikazio hori ere erabili nahi izan dugu gure formalizazioa ebaluatzeko. Beraz, testu libreetako izenen adieren artean desanbiguatzeko Dentsitate Kontzeptuala erabili dugu. Gaur egun pil-pilean dagoen gaia da hau, guztiz irekita jarraitzen duen arazoa. Itzulpen automatikorako 60.eko hamarkadan egin ziren sistemek adiera-desanbiguazioari ezin izan zioten aurre egin, eta hori izan zen beraien porrotaren arrazoietako bat. Erlazio-izaeraren inplementazioak informazio zabala erabiltzen hasi diren heinean, hitzen adiera-desanbiguazioan emaitza hobeak lortzen joan dira. Egungo teknologiarekin aplikazio errealetan aplikatzeko moduan egon ez arren, hurbil ikusten da edozein testutako hitzen adiera-desanbiguazio azkarra eta errore-maila onargarrikoa.

HADen hurbilpen hedatuenek polisemia eta homonimia adieren zerrenda itxi batez errepresentatzen dituzte, eta informazio xumea[1] soilik erabiliaz adiera egokia hautatzeko gai direla nabarmentzen dute. Badaude honen aurrean eszeptikoak direnak. Alde batetik daude HAD LNParen beste arazoetatik isolatuta ezin tratatu daitekeela diotenak, LNP orokorrerako beharrezko

[1] Xumea diogu ezagutza intentsiboa erabiltzen dutenekin alderatzen badugu. Beste era batera esanda, oraingo metodoek ezagutza estentsiboa erabiltzen dutela esan daiteke.

ezagutza guztia ezin delako alde batera utzi. LNPan aurrera egin ahala HAD naturalki ebatziko dela uste dute. Beste aldetik daude lexikoaren izaera dinamikoa aldarrikatzen dutenak. Horientzat metonimia eta metafora bezalako prozesuak ulertu gabe ezin da adieren arteko ezberdintasunik planteatu. Beste batzuk harantzago doaz, eta adieren artean mugak jartzerik ez dagoela diote, eta adieren beraien existentzia entitate diskretu bezala zalantzan jartzen dute. Gure ustez kritika horiek ikuspuntu ezberdinak besterik ez dira, kontuan hartu behar direnak, eta ahal dela HAD sisteman integratu beharrekoak (eta hau aldi berean LNP orokorrean integratu noski), baina ezin uka daiteke bitartean emaitza interesgarriak lortzen ari direla, eta HAD tratatu nahian teknika berritzaileak garatu izan direla. Nolabait badirudi eztabaida alde praktikora eraman dela, adieren existentzia bera zalantzan jartzen duen Kilgarriff-ek berak, *Senseval*[2] deritzon lehiaketa antolatu baitu HADaren inguruan 1998. urtean.

Gure ikerkuntza-taldean idazketarako laguntza-tresnak garatzea da helburu iraunkorretako bat. Bide horretatik Xuxen euskararako testu-zuzentzaile komertziala garatu genuen. Ortografia-erroreen aurrean programa zuzentzaileek erabiltzaileari hitz zuzena eskaintzen saiatzen dira, proposamen zerrenda baten bidez. Giza-erabiltzailearen esku dago proposamen zuzena aukeratzea. Testu-editoreen kasuan nahikoa bada ere, beste aplikazio batzuetan beharrezkoa da programak berak zuzenketa egokia aukeratzea. Halako aplikazioen adibide bat karaktere-ezagutza optikoa (*optical character recognition*) da. Jakina da, paperean dauden testuak ordenadorera pasatzea nahi baditugu karaktere-ezagutza optikoek ez dutela beti asmatzen (hitz hasieratako *I* adibidez *l* bezala interpretatzen dute sarritan), eta beraz post-prozesu bat egin beharra dagoela errore horiek zuzentzeko, normalean zuzentzaile ortografikoa erabiliz eta eskuz hautatuz aukera zuzena. Taldean garatu diren tresna sintaktikoen eta Dentsitate Kontzeptualaren bidez <u>testu-zuzenketa automatikorako</u> bidean saiakera bat egin dugu tesi honetan. Bide batez, erlazio-izaeraren neurria beste zeregin batean probatzeko aukera eman digu horrek.

Tesi lan honen beste motibazio garrantzitsu bat baliabide lexikalen sorrera da. 80.eko hamarkadan, ordurarte sintaxian buru belarri zegoen LNParen komunitatean, baliabide lexikal zabal eta aberatsen beharra zabaldu zen. LNPrako aplikazioak kalera atera ahal izateko testu errealei aurre egin beharra zegoen, eta horretarako ezinbesteko zen lexiko zabalak edukitzea. Bestalde, ordurarte erregela konplexu eta ugariren bidez deskribatzen ziren fenomeno linguistiko askok jatorri lexikala zutela jabetzean, lexikoa hitz zerrenda laua izatetik informazio aberats eta konplexua zuen sistema izatera pasatu zen. Gauzak horrela, lantaldeak lexiko horiek eskuz eraikitzen hasi ziren. Kodetu beharreko informazio kopurua itzela da eta gizon-urte askotako ahalegina suposatzen du, proiektu erraldoi

[2] http://www.itri.bton.ac.uk/events/senseval/

gutxi batzuen esku dagoena (adibidez CYC, EDR edo WordNet). Eskuzko kodeketaren alternatiba gisa, lexikoak edukiz betetzeko laguntza automatiko edo semi-automatikoak ere bilatu izan dira, eta horrekin arreta bestelako baliabide lexikalen tratamendura zuzendu zen, corpus eta hiztegietara.

Hiztegietatik Ezagutza-Base Lexikalak (EBL) erauzi izan dira. Erauzitako informazioaren artean, semantikari dagokionean, garrantzitsuena adieren arteko hierarkiak izan dira. Tamalez lantalde gehienek hitzen arteko hierarkiak besterik ezin izan dituzte lortu, ezin izan baitute automatikoki erabaki zein zen adiera egokia. Honen salbuespena LDOCE hiztegiarekin eginiko lana da, hiztegi konkretu horretan kodetuta dagoen informazio lagungarria erabiliz automatikoki eraiki baitute adieren arteko hierarkia. Erauzitako EBL gehienak ingeleserako izan dira, eskuz eraiki izan diren ontologia eta EBL erraldoiak bezala. Horrek gainontzeko hizkuntzak LNParen aurrean posizio ahul baten uzten ditu. Bi irtenbide osagarri daude egoera horren aurrean:

- hizkuntza bakoitzerako dauden corpus eta hiztegietatik abiatuta EBLak sortzea
- ingeleserako eraiki diren EBLetaz baliatzea beste hizkuntzatarako EBLak sortzeko

Hau da, hizkuntza bakoitzerako dauden baliabideetaz profitatu, nola ez, baina baita ere ingeleserako baliabideetan dagoen ezagutza interesatzen zaigun hizkuntzara nolabait itzuli. Gure ustez erlazio-izaeraren neurriaren formalizazioak bi irtenbide horietan lagundu dezake.

Orain arte aipatu ditugun bi motibazio nagusiak, erlazio-izaeraren formalizazioa eta baliabide lexikal egituratuen eraikuntza, uztartu egiten dira. Hizkuntza baterako erlazio-izaera ezin da definitu hizkuntza horretarako baliabide lexikal egituraturik ez badago, bereziki EBL eta ontologiak. Bestalde erlazio-izaera gabe ez da erraza baliabide lexikal egituratuak sortzeko laguntza-tresna automatikoak egitea. Ingelesarentzat eraiki izan diren EBL eta ontologiak erabiliaz posiblea da ingeleserako erlazio-izaera definitzea. Horretaz baliatuz, beste hizkuntzatan dauden baliabide egituratuen erauzte automatikoa azkartu eta ingelesera lotzea posible bada, orduan ingeleserako sortu diren baliabideetan dagoen aberastasuna xurgatu ahal izango da, eta baliabide aberats horiek beste hizkuntzetarako ere erabilgarriak izango dira. Ildo horretatik bi lan nagusi burutu nahi izan ditugu. Alde batetik gure taldean ikerkuntzaren objektu izan den *Le Plus Petit Larousse* frantses hiztegiko adierak WordNet ingeles EBLko adieretara lotu ditugu. Eta bestetik, hiztegian bertan dagoen informazioaz eta WordNetera egindako loturetaz baliatuz, LPPL-tik erauzitako hierarkiak desanbiguatu ditugu.

Tesi-lan honi ekin genionean ez zegoen baliabide lexikal egituratu zabalik ingelesa ez ziren hizkuntzentzat. Hori dela eta erlazio-izaera ingeleseko adierentzat definitu dugu, eta adiera-desanbiguazioa baita testu-zuzenketa ere ingeleseko testuen gainean egin dugu. EBLen aberasketa eta trinkotzeari dagokionean, frantsesezko hiztegi bat zegoen era sakonean landuta taldean, eta hori saiatu gara aberasten. Dena den, nahiz eta tesi honetan ezin landu izan dugun, euskara da garatutako teknika guztien azken jomuga, gure ikerkuntza taldean gertatzen den bezala. Jorratu ditugun bideak eta azterketak euskararako, edo orokorrean beste edozein hizkuntzarako, baliabide lexikal zabal baten eraikuntzarako funtsa dira.

I.B. Helburuak

Motibazio nagusiei erantzunez, erlazio-izaeraren formalizazioa eta baliabide lexikal egituratuen eraikuntza, bi helburu nagusi jarri dizkiogu tesi-lan honi:

a) teorikoa: ezagutzan oinarritutako hitz eta kontzeptuen arteko erlazio-izaera neurtzea
b) praktikoa: ingelesezkoak ez diren baliabide lexikal egituratuak aberastu eta trinkotzeko teknikak lantzea

Bi helburuak baliabide lexikalen inguruan dihardute. Helburu teorikoari dagokionez, baliabide lexikaletaz profitatzen saiatuko gara inferentzia mota bat aurrera eramateko. Helburu praktikoa baliabide lexikal aberatsagoen eraikuntzaz ari da, hiztegietatik EBLetara.

Helburu hauek gauzatzeko hiru eginkizun nagusi eraman ditugu aurrera:

1. WordNet-en oinarritutako Dentsitate Kontzeptuala diseinatu eta inplementatu.
2. Le Plus Petit Larousse frantses hiztegiko adierak WordNet-i lotu.
3. Le Plus Petit Larousse-etik erauzitako Hiztegi Ezagutza Baseko (HEB) adieren hierarkiak desanbiguatu eta trinkotu.

2. eta 3. eginkizunak aurrera eramateko beharrezkoa izan da Dentsitate Kontzeptuala erabiltzea. Aipatzekoa da, behin HEBko adieren hierarkia sendoa eraiki eta gero, posible izango dela Dentsitate Kontzeptuala zuzenean eraikitako hierarkia horren gain aplikatzea, frantseserako erlazio-izaeraren neurria lortuz. Gure hurbilpen honen atzetik honako hipotesia dago:

Ingelesezkoak ez diren EBLak sendotzeko kanpoko ezagutza behar dela, eta kanpoko ezagutza hori normalean ingelesez egon badagoenez, lotura eleanitzen bidez eskuratu daitekeela.

Goian aipatu bi helburu nagusiez gain, definitutako erlazio-izaeraren neurria beste bi arlotan aplikatu eta ebaluatu nahi izan dugu. Beraz goiko eginkizunetaz gain beste bi hauei ere aurre egin diegu:

4. Dentsitate Kontzeptualaren aplikazio, fintze eta ebaluazioa: hitzen adiera-desanbiguazioa
5. Dentsitate Kontzeptualaren aplikazio eta ebaluazioa: testu-zuzenketa automatikoa

Ingelesezko HAD burutzeko WordNet gainean inplementatutako Dentsitate Kontzeptuala besterik ez dugu erabili. Eginbehar honek berez duen interesaz gain, erlazio-izaera ebaluatzeko erabili dugu. Izan ere erlazio-izaera zuzenean ebaluatzeko metodo adosturik ez dago, eta nahiago izan dugu eginkizun praktiko eta konparagarri baten bidez ebaluatzea.

Testu-zuzenketa automatikoa aurrera eraman ahal izateko, WordNet gaineko Dentsitate Kontzeptualaz gain, ezagutza iturri ezberdinak erabili ditugu. Alde batetik sintaxiari buruzko ezagutza, eta bestetik hitzen maiztasun eta agerkidetzei dagozkien eredu estatistikoak.

I.C. Tesiaren egitura

Tesiaren helburu eta eginkizunekin kapitulu bakoitzak duen harremana, 1. taulan laburbildu dugu.

Tesiaren helburu nagusiak	Eginkizunak	Kapituluak
		I Sarrera
		II Baliabide Lexikalak
Ezagutzan oinarritutako hitz eta kontzeptuen arteko erlazio-izaera definitzea	WordNet-en oinarritutakok DK diseinatu eta inplementatu	III Erlazio-Izaera eta Dentsitate Kontzeptuala
	DK aplikazio, fintze eta ebaluazioa: hitzen adiera-desanbiguazioa	IV Hitzen Adiera-Desanbiguazioa
	DKren aplikazio eta ebaluazioa: testu-zuzenketa automatikoa	V Zuzenketa Automatikoa
Ingelesa ez diren hizkuntzetarako baliabide lexikal egituratuak aberastu eta trinkotzeko teknikak lantzea	*Le Plus Petit Larousse* frantses hiztegiko adierak WordNet-i lotu, eta *Le Plus Petit Larousse*-etik erauzitako HEBko adieren hierarkiak desanbiguatu eta trinkotu	VI Hiztegi Ezagutza-Basearen Aberasketa
		VII Ondorioak

1. taula: tesiaren egitura eta helburu nagusiak

Sarrera-kapitulu honen ondoren, **II. kapituluan** (Baliabide Lexikalak: Erabilera Praktikoak), baliabide lexikalei buruz hitz egingo dugu. Gaur egun Lengoaia Naturalaren Prozesamenduan baliabide lexikalak duten garrantzia aipatu ondoren, baliabide garrantzitsu eta ezagunenak aipatuko ditugu, arreta berezia eskainiz tesi honetan erabili ditugun corpus, hiztegi eta baliabide egituratuei. Hitzen adiera-desanbiguazioan *Semcor* eta *Brown* corpusetaz baliatuko gara emaitzak ebaluatzeko, eta testu-zuzenketan, aipatutakoez gain, *Bank of English* corpusa ere azalduko zaigu. Hiztegiei dagokionez *Le Plus Petit Larousse* eta *Oxford French-English Dictionary* erabili ditugu. Baliabide lexikal egituratuei dagokionean, WordNet – Dentsitate Kontzeptuala inplementatzeko aukeratu dugun hierarkia – beste ontologiekin alderatuko dugu.

III. kapituluan (Erlazio-Izaera eta Dentsitate Kontzeptuala) hitz eta adierak hertsiki erlazionatuta ote dauden neurtzeko moduak aztertu eta tesi-lan honen ekarpen nagusiena den Dentsitate Kontzeptuala aurkeztuko dugu. Dentsitate Kontzeptuala azaldu aurretik, erlazio-izaeraren bestelako formalizazioak aztertuko ditugu. Dentsitate Kontzeptualaren inplementazioa azaltzerakoan, enpirikoki erabaki beharreko parametro batzuk aurkeztuko ditugu. Ondoren ontologien gainean definitutako erlazio-izaeren nagusitasuna defendituko dugu, eta ontologiatan oinarritutakoen barruan Dentsitate Kontzeptualak dauzkan abantailak. Bukatzeko kapitulu honi dagozkion ekarpenak eta etorkizuneko eginkizunak aipatuko ditugu.

IV. kapituluan (Hitzen Adiera-Desanbiguazioa Testu Errealetan) Dentsitate Kontzeptuala aplikazio praktiko batean ebaluatu nahi izan dugu, eta bide batez aplikazio horren emaitzen arabera Dentsitate Kontzeptualaren parametroak doitu. Aurreko kapituluan Dentsitate Kontzeptualaren abantaila teoriko eta praktikoak azaltzen badira ere, aplikazio praktikoetan emaitza onak ematen dituela frogatu nahi izan dugu. Hitzen Adiera-Desanbiguazioan, testu bateko hitz bat bere zein adieratan erabiltzen den erabaki behar da. Erlazio-izaeraren neurri gehienak Hitzen Adiera-Desanbiguazioan (batez ere izenen desanbiguazioan) aplikatu izan dira, eta are gehiago, askotan horretarako diseinatu izan dira espreski. Kapitulu hau aurrekarien azterketa batez hasiko da, ezagutza-iturri ezberdinen beharra azpimarratuz. Ondoren gure esperimentuaren diseinua eta desanbiguatzeko Dentsitate Kontzeptuala erabiltzen duen algoritmoa azalduko ditugu. Aurrez aldetik desanbiguatuta dagoen corpus bat erabili dugu, automatikoki neurtu ahal izateko sistemaren doitasuna. Corpus horretako 4 fitxategi zoriz aukeratu ditugu, eta 2.000 inguru izen desanbiguatu ditugu, WordNet-eko adiera egokia esleituaz. Atal berezi bat erabiliko dugu Dentsitate Kontzeptualaren parametroen eragina aztertzeko, eta parametroentzako balio hoberenak aukeratzeko. Emaitzen ebaluazioaren ondoren, beste metodoekin alderatu dugu. Ontologian oinarritutako beste bi metodo inplementatu eta aplikatu ditugu, emaitza okerragoak lortuaz. Bukatzeko, kapitulu honen ekarpen eta etorkizunerako lanak.

V. kapituluan (Zuzenketa Automatikoa) beste aplikazio praktiko bat landu dugu idazketa-erroreen zuzenketa automatikoaren inguruan. Kapitulu honetan zuzenketa-proposamenen artean zuzena automatikoki aukeratzen saiatzen den sistemaren diseinu eta inplementazioa aurkezten ditugu. Lehenbizi aurrekarien azterketa egin dugu. Ondoren sintaxi eta semantikan oinarritutako bideragarritasun-azterketaren emaitzak aurkezten ditugu. Ondorio bezala semantikaren ekarpena ezinbestekotzat jo genuen. Gure algoritmoan errorea azaltzen den esaldi eta testuinguruari erreparatuko diogu proposamen zuzena aukeratzeko orduan. Lehenbizi egitura sintaktiko onargarria ematen ez dituzten proposamenak baztertuko ditugu. Gainontzeko proposamenen artean esanahiaren aldetik testuinguruan zentzu gehien egiten duena aukeratu ahal izateko ezagutza semantikoa erabiliko dugu. Alde batetik WordNet-en dagoen ezagutzaz baliatzeko izenen arteko Dentsitate Kontzeptuala erabili dugu, bide batez Dentsitatearen ekarpena neurtuko dugularik. Beste aldetik corpusetan oinarritutako teknikak ere erabiliko ditugu. Ebaluazioa bi corpus ezberdinen gainean egin dugu: artifizialki sortutako erroreen corpusa eta corpus naturala. Bukatzeko, beste kapituluetan legez, ekarpenak eta etorkizunerako lana azaldu ditugu.

VI. kapituluan (Hiztegi Ezagutza-Basearen Aberasketa) tesi honen beste helburua den ingelesa ez diren hizkuntzetarako EBLen aberaste eta trinkotzea jorratu dugu. Lehenbizi aurrekariak aztertuko ditugu, eta hiztegietatik erauzitako hierarkiek dauzkaten arazoak azaldu. Kontuan hartu behar da hierarkia horiek ez direla guztiz desanbiguatuta egoten. Gainera, erauzitako hierarkiak sakonera apalekoak izan eta elkarrengandik isolatuta egoten dira, eta hierarkiaren goi-mailan koherentzia arazoak gertatzen dira. Arazo hauen iturburu dira, hein batean, hierarkian gertatzen diren bigiztak eta adiera batzuek hierarkian ezin kokatu izana, erlatore berezien bidez definitzen direnak hain zuzen ere. Aurrekarietan baliabide lexikal eleanitzen arteko lotura ere begiratu dugu. Ondoren gure hurbilpena azaldu dugu.

EBLen eraikuntza sendotzea posiblea den ala ez ikusteko frantseseko *Le Plus Petit Larousse*-etik erauzitako Hiztegi-Ezagutza Basea erabili dugu. HEB hori LNPrako EBL bezala erabili ahal izateko arestian aipatutako arazoak konpondu beharko lirateke. Bi arazo horiei era bateratu batez erantzuten saiatu gara. Hasteko, bigizta eta erlatore bidezko definizioak aztertu ditugu eta horiek LPPLra lotu ahal izateko, kanpoko EBL batera lotu ditugu LPPLko adiera guztiak. Gure kasuan WordNet hautatu dugu kanpoko EBL bezala. Ondoren hierarkiak automatikoki desanbiguatu ditugu. Azkenik, LPPL-WordNet lotura erabili dugu hierarkiak elkarrekin harremanetan jartzeko, bide batez goi-mailako koherentzia falta ere konponduaz.

LPPLtik erauzitako HEBa WordNet-i lotzeko hiztegi elebidun bat erabili dugu, hizkuntzen arteko zubi bezala. Lotura automatikoki egin ahal izateko Dentsitate Kontzeptualaz baliatu gara, LPPLko adiera bakoitzari WordNet-eko kontzeptu bat (edo gehiago) esleitzeko balioko diguna. Hierarkia desanbiguatzeko hiztegian bertan dagoen ezagutzaz eta WordNet-i egindako loturez baliatu gara. Hainbat teknika independente erabili ditugu, Dentsitate Kontzeptuala barne, eta teknika horiek konbinatu ondoren adiera egokienak aukeratu ditugu. Bukatzeko, kapitulu honetan eginiko ekarpenak eta etorkizunerako lana bildu ditugu.

Kapitulu bakoitzean tesi-lan honen ekarpenak adierazten saiatu gara. Azkeneko kapituluan horiek guztiak bildu eta etorkizunean egin daitezkeen hobekuntzak ere aipatzen ditugu.

Mamiarekin hasi aurretik, tesi honen garapenean argitaratutako artikuluen irakur gida azaldu nahi dugu. Irakur gida honetan, artikulu bakoitzak tesi honen egituran duen lekua zein den adierazten dugu, eta bide batez artikuluen zerrenda aurkeztu ere.

	Kapitulua	Atala	Artikulua
III	Erlazio-Izaera eta Dentsitate Kontzeptuala	B.1	(Agirre et al., 1994b) (Agirre & Rigau, 1995) (Agirre & Rigau, 1996a) (Agirre & Rigau, 1996b)
IV	Hitzen Adiera-Desanbiguazioa		(Agirre & Rigau, 1995) (Agirre & Rigau, 1996a) (Agirre & Rigau, 1996b)
V	Zuzenketa automatikoa	B.1	(Agirre, 93)
		B	(Agirre et al., 1994b) (Agirre et al., 1995)
		C	(Agirre et al., 1998b) (Agirre et al., 1998c)
VI	Hiztegi Ezagutza-Basearen aberasketa	C.1	(Rigau & Agirre, 1995)
		D	(Rigau et al., 1997)

II. Kapitulua

BALIABIDE LEXIKALAK: ERABILERA PRAKTIKOAK

Sarreran aipatu dugu tesi honetako helburuen atzean baliabide lexikal egituratuen eraikuntza eta erabilera dagoela. Kapitulu honetan baliabide lexikalak lau sailetan banatuko ditugu. Sail bakoitzeko baliabide ezagun eta erabilienak II.A. atalean aipatuko ditugu. Horiek azaldu ondoren, ontologiak, Ezagutza-Base Lexikal (EBL) eta Hiztegi Ezagutza-Baseak (HEB), sail berdinean sailkatzeko arrazoiak aztertuko ditugu (II.B. atala). Bukatzeko, tesi honetan erabili ditugun baliabide lexikalen ezaugarriak azalduko dira.

II.A. Baliabide lexikal motak

Baliabide lexikalak lau sail nagusitan banatu ditugu:

1. Corpusak
1. Hiztegiak
2. Egituratuak: ezagutza-base lexikalak eta hiztegi ezagutza-baseak
3. Egituratuak: ontologiak

Sailkapen honetako ordena informazioaren elaborazio-mailaren arabera egin dugu. Corpusetan hitzei buruzko informazio gordina dago. Hiztegietan, aldiz, lexikografoek kategoria, erabilera kodeak, definizioa, adibideak, etab. biltzen dituzte. Hitzak ez ezik, hitzen adierak ere azaltzen zaizkigu. HEBetan hiztegietan dagoen informazio inplizitua esplizitu bihurtu eta hitzei buruzko informazio lexikala biltzen da. EBLetan LNPrako sistema batek ulermen eta sormena egiteko hitzei buruz behar duen informazio guztia biltzen dute. Ontologiak munduari buruzko kontzeptualizazioak dira, munduari edo alor konkretu bati buruz jakin beharrekoak (gauza, gertakizun, arrazonamendu, eta abar, sen ona azken finean) biltzen saiatzen direnak.

II.A.1. Corpusak

Linguistikaren barruan aspalditik izan dira linguistika enpirikoa aldarrikatu dutenak. Hauentzat, linguistika ahozko edo idatzizko hizkuntzaren azterketa enpirikoan oinarritu beharko litzateke (McEnery & Wilson, 1996). Idatzizko hizkuntzaren kasuan, azterketaren subjektua idatzizko corpus batek osatzen du. Testu multzo bat corpus izateko lau baldintza jartzen diote McEnery eta Wilson-ek: lagin errepresentatiboetan oinarritua egotea, tamainaz finitua izatea eta makinek tratatzeko modukoa izatea. Corpusek, gainera, errepresentatzen duten lengoaia-aldaeraren erreferentzia estandarra izateko bokazioa eduki beharko lukete.

Corpusetan oinarritutako linguistikak kritika zorrotzak jaso zituen 50. hamarkadan, iharduera asko murriztu zelarik. 80. hamarkadatik aurrera, ordea, onarpen zabala jaso izan du. Zalantzarik gabe, ordenadoreen ahalmena eta makinaz tratatu daitezkeen testuen kopurua etengabe hazten joatea, besteak beste, daude linguistika enpirikoaren berragerpenaren atzean. Gaur egun linguistikaren alor guztietara zabaldu du bere eragina, ezagutza-baseen aberasketara eta hitzen eta kontzeptuen arteko erlazio-izaeren ikerkuntzara ere. III., IV., V. eta VI. kapituluetan ikusiko ditugu corpusetan oinarritutako tekniken adibide batzuk.

Ingeleserako erreferentzia-corpus ugari sortu izan dira. Estatubatuarrak izan ziren aitzindari, Brown deritzon corpusarekin (Francis & Kucera, 1967). Bretainia Handiko ingelesarentzat ondoren etorri zen London-LUND corpusa (Svartvik, 1990), eta orduz gero etengabe ari dira corpusak berritu, sortu eta aberasten. Corpusean berez hitzak besterik ez daude, testu gordinak, baina corpusen erabilera asko zabaltzen da informazio linguistikoa gehitzen badiegu. Informazio hori hitzen kategoria izan daiteke, edo esaldien egitura sintaktikoa (adibidez, Penn Treebank delakoa edo Birmingham-eko *Bank of English* corpusa[3], Murrizpen-Gramatiken bidez (Karlsson et al. 1995) kategoria eta egitura sintaktikoz etiketatu dena), edo informazio semantikoa (aurrerago aipatuko dugun *SemCor*[4], hitzen adierez etiketatu den Brown corpusaren azpimultzoa, Miller et al. 1993a). Euskararako Euskaltzaindiak UZEIren laguntzaz bildu izan du Egungo Euskararen Bilketa Sistematikoa, gerra ondorengo testuen laginez osatutako miloi bat hitzetako corpusa (Urkia & Sagarna, 1990). IXA taldea euskara estandarra biltzen duen corpus zabalago bat biltzen ari da.

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[3] http://titania.cobuild.collins.co.uk/boe_info.html

[4] http://www.cogsci.princeton.edu/~wn/

Tesi lan honetarako erabili ditugun corpusak Brown (ikus IV. eta V. kapituluak), Semcor (IV. kapituluan) eta Bank of English (V. kapituluan) dira. Aurrerago ikusiko ditugu hauei buruzko datu gehiago.

II.A.2. Hiztegiak

Lengoaia Naturalaren Prozesamenduan, 80. hamarkadarainoko sistemetan ahaleginaren gehiengoa sintaxi-egituretara eta sintaxitik semantikarako zubietara mugatzen zen. Lexikoa arazorik gabe beteko litzatekeen hitz zerrenda soil bat besterik izango ez zela uste zen. Garai horretan konturatu ziren LNPrako sistemen hedakuntzarako arazo nagusiena lexikoa urriegia izatea zela, eta lexikoa edukiz betetzea uste baina lan neketsuagoa zela. Garai berdinean, formalismo sintaktiko berri batzuk egitura sintaktikoen pisua lexikoira pasatzen hasi ziren, lexikoaren egitura konplexuago bihurtuz.

Lexiko zabal eta konplexuen eraikuntza eskuz egitea gehiegizko lana izango zela eta, hiztegietan zegoen informazioa ustiatzen ahalegindu ziren. Hiztegi elebakarretan hitzen kategoria, azpikategoria, definizioa, erabilera adibideak, etab. aurkitu daitezke. Gainera hitzen esanahiak antolatuta daude, adieren bidez. Thesaurus izeneko hiztegietan hitzak eremu semantikoen arabera multzokatuta daude, aurretik emandako sailkapen bat jarraituz. Berrikiago, hiztegi elebidunetan dagoen informazioa ere ustiatzen hasi da, bai hizkuntza batetik besterako ordainak, baita hizkuntza bateko kolokazio edo eremu semantikoa bezalako informazioa ere.

Hiztegi elebakarren artean, bat izan da tratatua bereziki, *Longman Dictionary of Contemporary English* deritzona (LDOCE, Procter, 1978). Bertako definizioak hiztegi mugatu bat erabiliaz egin dira, ingelesa ikasten ari direnentzat pentsatua. Bestalde, aditzen azpikategorizazioari buruzko informazioa, izenen kode pragmatikoak, arlo semantikoari buruzko kode semantikoak, eta abar jasotzen ditu. Lengoaia naturalaren prozesamenduan aipatzen diren beste hiru hiztegi *The Webster's Seventh New Collegiate Dictionary* (W7, Gove, 1969), *Oxford Advanced Learner's Dictionary of Current English* (OALDCE, Hornby, 1974) eta *Collins COBUILD English Language Dictionary* (CED, Sinclair, 1987) dira. Ingelesa ez diren hizkuntzatan hiztegi gutxi tratatu izan dira. Gaztelerarako, adibidez, *Diccionario General Ilustrado de la Lengua Española* (DGILE, Alvar, 1987) da formatu elektronikora pasatu den gutxietakoa. Frantseserako *Le Plus Petit Larousse* (LPPL, Larousse, 1980) dago, gure taldean analizatu izan dena eta tesi honetan landu duguna. Euskararako, *Euskal Hiztegia* (Sarasola, 1997) dago formatu elektronikoan.

Hiztegi hauen erabilera nagusiak, bertatik informazio sintaktikoa erauztea (adibidez, ALVEY-ko lexikoa horrela eraiki zuten, Boguraev & Briscoe, 1987) eta haiekin HEB edo EBL bat eraikitzea litzateke, hurrengo atalean ikusiko dugun bezala (VI. kapitulua ere aztertuko ditugu saiakera hauek).

Beste hiztegi mota bat thesaurusak dira, sarrerak eduki semantikoaren arabera antolatuta dauzkatenak. Lengoaia naturalaren prozesamenduan *Roget's Thesaurus* (Kirkpatrick, 1987) dezente erabili izan da.

Hiztegi elebidunen artean Collins argitaletxeak ingeles-gaztelania, ingeles-frantses, ingeles-italiera, eta abar eskuragarri dauzka formatu elektronikoan. Gaztelania eta ingelesaren artean ere bada *Diccionario Vox/Harrap's Esencial Español-Inglés* (Biblograf, 1992). Tesi lan honetan *Oxford French-English Dictionary* (OFED, OUP, 1989) erabili dugu. Euskarari dagokionean Elhuyarren euskara-gaztelania hiztegia (Elhuyar, 1996), Aulestia eta White-en euskara-ingelesa hiztegia (Aulestia & White, 1992) eta Morris-en euskara-ingeles hiztegia (Morris, 1998) formatu elektronikoan dauzkagu IXA taldean.

II.A.3. Ezagutza-base lexikalak eta hiztegi ezagutza-baseak

Lengoaia naturalen prozesamendu sintaktiko eta semantikoa egin ahal izateko, lexikoiak hitz zerrenda izatetik EBL izatera pasatu dira, hitz eta adierei buruzko informazioa dutenak. EBL baten hizkuntza ulertu ahal izateko ordenadoreak hitzei buruz jakin beharreko guztia egon beharko litzateke (Yokoi, 1995). EBLen ezaugarri garrantzitsuena heredentzia izaten da, adierak klase/azpiklase hierarkien inguruan antolatzen dira eta (Copestake, 1990). EBLak eskuz eraiki daitezke, adibidez WordNet (Miller et al., 1993b) eta EDR (EDR, 1993), baina askotan hiztegietatik erauzten dira (Copestake, 1990; Bruce et al. 1992).

LNParen beste ikuspuntu batetik, HEBek hiztegietatik erauzitako informazioa jasotzen dute (Artola, 1993). Erauzitako informazioaren artean, hemen ere, adieren hierarkiak dira aipagarriak. HEB batetik EBL bat eratorri daiteke, hiztegitik zuzenean EBL eraiki daitekeen bezala. HEB baten enfasia hiztegiko informazioan da, inplizitu egon eta esplizitu bihurtu dena, giza erabiltzaileak edo programa batek erabiltzeko moduan. EBL baten enfasia, ordea, LNP aplikazioetarako baliagarria izatea da. Tesi honi dagokionez, erlazio-izaera definitzeko beharrezko informazioa duten heinean ez gara gehiegi arduratuko EBL edo HEB bat denentz, eta ez ditugu bereiziko.

EBL eta HEBak eraikitzeko, hiztegietatik erauzi izan den informazio semantikoa definizioen azterketatik etorri ohi da batez ere, adieren hierarkia eratuz, eta hitzen (edo adieren) arteko bestelako erlazio lexikal-semantikoak finkatuz. Lehenbizi definizioen analisi sintaktikoa egin behar da, eta ondoren analisiaren emaitzatik erlazio lexikal-semantikoen erauzketa. Erlazio horietan azaltzen diren hitzen desanbiguazioa ere egin behar da, adieren arteko erlazioak eduki ahal izateko. Honi buruzko zehaztasun gehiago ikusiko ditugu VI. kapituluan.

Atal honetan banan-bana ikusiko ditugu eskuz eraiki diren EBL batzuk (WordNet, EuroWordNet, Item eta EDR direlakoak) eta hiztegietatik egindako erauzketa automatikoan aritu diren proiektu batzuk (Acquilex, Nounsense, MindNet eta Hiztsua). Arlo honetan egin izan diren lanak ugariak izanda, ez gara zerrenda exhaustiboa egiten saiatu, esanguratsuenak biltzen baizik. Hiztegien erauzketari buruzko lan gehiago VI. kapituluan aipatuko ditugu.

II.A.3.a) WordNet, EuroWordNet eta Item

WordNet EBLa (Miller et al. 1993b) sinonimiaren inguruan antolatuta dago. Sinonimo multzo bakoitza, *synset* deritzona, hitzen adieraz eratuta dago, eta kontzeptu bat errepresentatzen du. WordNet-eko synset-en artean erlazio lexikal anitz daude, baina batez ere hiperonimia eta meronimia dira landuta daudenak. Synset-ak berez hierarkiatan antolatzen dira, baina multzo semantiko nagusietan ere multzokatuta daude. Izenen kasuan 15 eremu semantiko bereizten dira. Kontzeptu kopuruari dagokionez, WordNet 1.5 bertsioan orotara 91.591 kontzeptu daude 126.520 hitzentzat, izenen kasuan 60.557 kontzeptu eta 87.642 izen. WordNet edozeinek eskuratu dezake Internet bidez[5], eta gaur egun oso erabilia da LNP inguruko ikerkuntzan (artikuluen zerrenda bat ikusi daiteke WordNet-eko amaraun-orrian). Guk ere WordNet erabili dugu adieren arteko erlazio-izaera definitzeko (ikus III. kapitulua). Hurrengo atalean, WordNet-i buruzko zehaztasun gehiago ikusiko ditugu.

EuroWordNet[6] (Vossen, 1997) proiektua 1996an hasi eta 1999raino luzatuko den proiektu europarra da. EBL honek WordNet-en diseinuaren antzekoa erabiltzen du, baina Europako zortzi hizkuntzatara zabaltzen da. WordNet-en baino hizkuntza barneko erlazio mota gehiago daude, batez ere kategoria ezberdinen artekoak. Oraindik edukia guztiz bete gabe dago, baina dirudienez hemen ere batez ere hiperonimia erlazioa izango da landuena. Hizkuntzaren barne-erlazioez gain, kontzeptuak WordNet-eko synset-era lotuta daude, *Inter-Lingual Index* deritzonaren bidez, hizkuntzen arteko ordainak errepresentatuz. Horretaz gain, hizkuntzatik aparteko moduluan Goi-ontologia bat (*top ontology)* eta Domeinu-ontologiak (*domain ontology*) ere badaude. Lehenbizikoak WordNet ezberdinen goi aldeko synset-ak ezaugarri semantikoen arabera sailkatzea ahalbideratzen du, eta nolabait esateko, WordNet-en eremu semantikoen papera jokatzen du, nahiz eta motibazio

[5] http://www.cogsci.princeton.edu/~wn

[6] http://www.let.uva.nl/~ewn/

linguistiko sakonagoak hartu diren kontuan. 63 kontzeptu edo ezaugarri semantikok osatzen dute goi-ontologia hau. Hizkuntza bakoitzerako edukia, dagokion taldeak eskura dauzkan baliabideez baliatuz betetzen dute. Oraingoz ez dago edukien kopuruaren berririk, baina bai talde guztien artean adostutako oinarrizko kontzeptuen zerrenda, 1024 kontzeptuz osatua dagoena.

Donostiako Informatika Fakultateko Lengoaia Naturalaren Prozesamendurako IXA taldea[7] EuroWordNet proiektura lotuta dago, kanpoko eraikitzaile bezala. Horren inguruan, eta Estatu mailako ITEM proiektuaren[8] barnean, Euskararako WordNet-a eraikitzen ari gara EuroWordNet-eko diseinua jarraituaz. EuroWordNet-eko gaztelera eta euskararako WordNet-en eraikuntza automatikoan erabiltzen ari diren teknikak, tesi lan honen VI. kapituluan ikusiko ditugunen antzekoak dira, guk frantseseko hiztegia WordNet-i lotzeko erabili ditugunei hertsiki lotuak.

II.A.3.b) EDR

Japoniako ikerkuntza-agentziak, itzulpen automatikoan lexikoaren garapenak zeukan garrantzia ikusita, *Japan Electronic Dictionary Research Institute* sortu zuen 1986 urtean, japoniera eta ingelesaren tratamendu automatikorako lexikoa eraiki zezaten (Yokoi, 1995; EDR 1993). Proiektu erraldoi honek 9 urte ondoren bere emaitzak salmentan jarri zituen. Hizkuntza bakoitzerako corpusa, agerkidetza eta esaldi analizatuen baseak bildu zituzten, eta 300.000 hitz inguruko lexikoiak eraiki. Horretaz gain lexikoi elebidunak eta 4.000.000 kontzeptu biltzen dituen EBLa ere sortu dituzte. Kontzeptuak biltzen dituen ezagutza-baseak kontzeptuen deskribapenak eta kontzeptuen arteko erlazio lexikal anitz biltzen ditu, hierarkia osatzen duen azpiklase erlazioa izanik garrantzitsuena.

II.A.3.c) Acquilex

Acquilex[9] (Briscoe et al. 1993) proiektuaren helburua hiztegi elektronikoetatik (elebakar eta elebidunak) informazio lexikala erauzteko tresna eta metodologia automatikoak garatzea zen, Europako lau hizkuntzarentzat. Hiztegietatik erauzitako informazioarekin LNPrako aplikazioetarako EBL eleanitz baten prototipoa sortu zuten. Adibidez, izenetan janariari buruzko azpimultzoa landu zuten, ingeleserako 1.000 eta beste hizkuntzatarako 300 adiera inguru tratatuaz. Hiztegi elebakarretatik egindako erauzketa automatikoaren enfasia hierarkien eraikuntzan jarri zuten, nahiz eta bestelako atributu eta erlazioak erauzten ere saiatu. Hierarkia automatikoki eraikitzeko orduan ez zuten adiera-desanbiguaziorako irizpide automatiko garbirik proposatu (Copestake, 1990).

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7 http://ixa.si.ehu.es/

8 http://sensei.ieec.uned.es/item/

9 http://www.cl.cam.ac.uk/Research/NL/acquilex/

II.A.3.d) NounSense

NounSense LDOCE hiztegitik erauzi den EBLaren izena da (Wilks et al. 1996; Bruce et al. 1992). NounSense-en, hitzen definizioetako testuez gain, LDOCE-n dauden kode pragmatiko eta semantikoetatik erauzitako informazioa ere dago. Enfasi handiena izenen hierarkia eraikitzean jarri da eta horretarako hiztegiko definizioak analizatu eta desanbiguatu ondoren hiperonimia erlazioa erauzten da adieren artean. Emaitza bezala 39.000 adieren arteko hierarkia lortu zuten.

II.A.3.e) MindNet

MindNet (Richardson, 1997) LDOCE eta *American Heritage Dictonary* hiztegietatik erauzitako informazioaz eraiki da. Definizioetatik hiperonimiaz aparte beste 23 erlazio ere erauzi izan dira, izen, adjektibo eta aditzentzat, adierak desanbiguatu egin direlarik. Horrek ez du berrikuntza gehiegizkorik suposatzen berez, Acquilex, NounSense, eta beste hainbat proiekuetan ere planteatu izan da eta. Baina MindNet da teknika horien aplikazio zabalez eginiko lehenbiziko EBLa, eraginkortasun handia omen duena. Emaitza 191.000 adieratako sare semantikoa da.

II.A.3.f) Hiztsua eta Anhitz

Hiztsua (Artola, 1993) *Le Plus Petit Larousse* (LPPL) hiztegitik erauzitako Hiztegi Sistema Urgazle Adimentsua da. Bere funtzionalitatearen oinarrian automatikoki sortutako HEB aberats bat dago. Hiperonimia erlazioaren inguruan antolatuta dago batez ere baina beste 14 erlazio ere erauzi ziren, izen, aditz eta adjektiboentzat. LPPL-ko adiera guztietatik, nahiz eta denak analizatu, 6.130 adiera sartu ziren HEBan. Tesi honetako IV. kapituluan, kopuru hori zabaldu eta izenen 13.740 adierentzat eratorriko dugu hierarkia desanbiguatua. Aurrerago aipatuko ditugu HEB honen ezaugarri gehiago.

Hiztsua HEB elebakarra bada, Anhitz proiektuan (Arregi, 1995) eleaniztasunaren dimentsioa eransten zaio. Horretarako frantses eta euskarazko bi HEB elebakarren arteko zubia eraikitzen da, hiztegi elebidunetan oinarrituz. Itzulpengintzarako laguntza den sistema honen prototipoak 168 hitz eta 305 kontzeptu dauzka euskarazko partean eta 541 hitz eta 1139 kontzeptu frantseseko zatian. Horien artean 556 lotura elebidun landu dira.

II.A.4. Ontologiak

Arestian esan dugun bezala, ontologiak mundu errealaren kontzeptualizazioak dira, mundu errealari buruzko inferentziak egiteko gaitasuna dutenak. Definizio lauso hau aukeratu dugu, Adimen Artifizialaren arloan definizio zehatzagoek kontrobertsia pizten baitute, eta tesi honi dagokionean ontologien ezaugarri bat izango delako guretzat garrantzitsuena: hierarkia darabiltela bizkarrezur bezala. Ontologiak aplikazio askotarako eraiki izan dira (softwarearen berrerabilgarritasuna, medikuntzako sistema-adituak, datu-base heterogeneoen integrazioa, lengoaia naturalen sorkuntza, ulermen, itzulpen, eta abar), eta normalean eremu espezifikoetarako eraiki ohi dira. Hala ere, badira ezagutza orokorragoa biltzen saiatzen direnak ere, adibidez Mikrokosmos, Sensus, CYC, etab. Ikus ditzagun ontologiak definitzeko egin diren saiakera batzuk:

> *Ontology ia a model of the world; an ontology defines the ways in which concepts are related, their relative significance, and their dependencies. The most significant relationship between concepts in the ontology is that of "hyponym/hypernymy" which determines if a concept belongs to the class defined by another concept.* (Onyshkevich & Nirenburg, 1994)

> *Ontologies are often equated with taxonomic hierarchies of classes, class definitions, and the subsumption relation, but ontologies need not be limited to these forms. … The word "ontology" seems to generate a lot of controversy in discussions about AI. It has a long history in philosophy, in which it refers to the subject of existence. It is also often confused with epistemology, which is about knowledge and knowing. …In the context of knowledge sharing, I use the term ontology to mean a specification of a conceptualization. That is, an ontology is a description (like a formal specification of a program) of the concepts and relationships that can exist for an agent or a community of agents. This definition is consistent with the usage of ontology as set-of-concept-definitions, but more general. And it is certainly a different sense of the word than its use in philosophy* (Gruber, 1993)[10]*:*

> *An ontology is a specification of a conceptualization. … is a logical theory whose models constrain a particular conceptualization, without exactly specifying it…. In many cases, the axioms of an ontology only express subsumption (ISA) relationships between unary predicates, but of course a more detailed axiomatization is often necessary in order to exclude unwanted interpretations* (Guarino, 1997)

[10] http://www-ksl.stanford.edu/kst/what-is-an-ontology.html

Autore guztiak daude ados ontologiak oso hetereogeneoak direla esatean, norberaren beharretara neurrira eginak. Hala ere, ontologia denek edukitzen dute kontzeptu zerrenda bat eta kontzeptu horien arteko hierarkia, klase/azpiklase erlazioak egituratuta dagoena. Hori izaten da ontologien ezaugarririk garrantzitsuenetakoa, goian aipatutako definizio guztietan azaltzen dena. Ikus ditzagun Lengoaia Naturalaren Prozesamenduarekin zerikusia duten ontologia garrantzitsuenetako hiru, eta ondoren arituko gara ontologia eta HEB/EBLen arteko berdintasun eta ezberdintasunei buruz.

II.A.4.a) Mikrokosmos

Mikrokosmos-eko[11] ontologia (Onyshkevich & Nirenburg, 1994) Ontos zeritzon ontologiatik abiatuta garatu izan da. Mikrokosmos ezagutzan oinarritutako itzulpen automatikorako proiektua da. Sistema honetan lexikoia eta ontologia bereizi egiten dira. Lehenbizikoan informazio morfologikoa, sintaktikoa, eta abar dago, baita ere semantikari buruzko zenbait informazio ere. Ontologian munduari buruzko ohiko kontzeptualizazioa dago. Lexikoko hitzen eta ontologiako kontzeptuen arteko harremana ez da sinplea. Kasu sinpleenean hitzaren adiera bati ontologiako kontzeptu bat egokituko zaio, adibidez, *dog-n1* adierari *%dog* kontzeptua dagokio. Kasu konplexuagoetan ontologiako kontzeptura dagoen loturaz gain, kontzeptuari murrizpen osagarriak gehitzen zaizkio, adibidez, *eat-v1* adierari *%ingest* kontzeptua dagokio, baina honelako murrizpenekin: aditzaren subjektua ekintzaren agentea izan eta *%animal* kontzeptu azpian egon behar du ontologian (hautapen-murrizpena). Ezagutza semantikoari dagokionean beraz, kontzeptuen hierarkia ontologian dago, eta murrizpen eta hitz-kontzeptu loturak aldiz lexikoan.

Mikrokosmos-eko autoreen arabera ontologia bat ezin da egon *adieratan* oinarrituta, praktikoa izateko kontzeptu gehiegi egongo bailirateke ontologian[12]. Bestalde, ez zaie iruditzen unitate lexikalen esanahia primitibo gutxi batzuen bidez deskonposatzea bideragarria denik, eta lexikoko sarrerak konplexuegiak egingo lituzkeela diote. Horregatik eduki semantikoa ontologia eta lexikoaren artean banatu behar dela uste dute.

Ontologiak 4.500 kontzeptu dauzka[13], eta hiperonimiaz gain beste erlazioetan ere aberatsa da, kontzeptu bakoitzak batez-beste 14 erlazio dauzka eta. Horretaz gain, lexikoan ere badaude bestelako erlazioak ere, adibidez hautapen-murrizpenak.

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[11] http://crl.nmsu.edu/Research/Projects/mikro/index.html

[12] Hobbs-ek (1995) *ontological promiscuity* deitzen zion honi.

[13] Lexikoian dauden adieren kopurua ezin izan dugu inon topatu.

II.A.4.b) Sensus

Sensus[14] (Hovy & Nirenburg, 1992), itzulpen automatikorako Pangloss[15] sistemaren ontologia da. Beste ontologia eta baliabide lexikalen bategitearen bidez sortu zen: Penman Upper Model (Bateman, 1990), Ontos (Mikrokosmosen aurretikoa), LDOCE eta WordNet. Ontologiaren goi aldea, *Ontology Base* deritzona, prozesamendu linguistikorako beharrezkoak diren desberdintasunak jasotzen dituzten 400 kontzeptuz osatuta dago. Ontos eta Upper Model-eko kontzeptuak eta izenen kasuan LDOCE-ko kode semantikoak eskuz bilduz sortu zen. Ontologiako gainontzeko kontzeptuak automatikoki gehitu dituzte WordNet-etik, Knight eta Luk-en (1994) artikuluan adierazten den bezala. Guztira 70.000 kontzeptu inguru dauzka ontologiak. *Ontology Base* deritzonean erlazio aberatsak daude, baina gainontzeko kontzeptuentzat hiperonimia besterik ez dago. Ontologia honi ingelesezko 90.000 hitz, japonierazko 120.000 hitz eta gaztelerazko 40.000 hitz lotu dizkiete.

II.A.4.c) CYC

CYC 13 urte baina gehiagotan lanean aritu den proiektu erraldoia izan da (Lenat, 1995)[16], pertsonok dugun sen ona ezagutza-base batean islatu nahi izan duena. Bere helburua ez da Lengoaia Naturalaren Prozesamendua bakarrik, Adimen Artifizialean planteatu izan diren arazo latz askori erantzun nahi izan baitio. Horretarako 100.000 kontzeptu eta kontzeptuen instantziei buruzko 1.000.000 bat baieztapen sartu izan dira ezagutza basean. CYC-eko lexikoan 14.000 lema daude. Duela gutxi ezagutza-basetik 3.000 kontzeptutako ontologia erauzi dute, edonork erabili dezan (ezagutza-base osoa erabiltzeko ordaindu beharra dago). Ontologia murriztu horretan klase/azpiklase eta instantzia-erlazioak besterik ez daude.

II.B. Ontologiak eta HEB/EBLak

Tesi honetan zehar, eta batez ere erlazio-izaera aztertzen duen III. kapituluan, ontologiei buruz arituko gara era zabalean, eta HEB eta EBLak ontologia bezala ere sailkatuko ditugu. Aurreko atalean ontologiak aztertu izan ditugunean, nabaria izan da kontzeptuen arteko klase/azpiklase hierarkiak duen garrantzia. HEB eta EBLetan ere erlazio hau da ezagutza-basea egituratzen duena, nahiz eta adieren arteko hiperonimia/hiponimia deitu.

Autore batzuk ontologia eta HEB/EBLen arteko diferentziak azpimarratzen saiatu dira, eta ez ditugu guk horiek ukatuko: kontzeptu guztiak lexikalizatuak egon behar duten edo ez, hierarkiaren

[14] http://www.isi.edu/natural-language/resources/sensus.html

[15] http://www.lti.cs.cmu.edu/Research/Pangloss/

[16] http://www.cyc.com/

goi aldearen antolatzeko irizpideak linguistikoak soilik diren edo ez, eta abar. Hala ere beraien arteko mugak ez daude garbi. Adibidez, EAGLES-eko lexikoari buruzko taldeak bere behin-behineko barne-txostenean[17] WordNet ontologiatik hurbil ikusten du, nahiz eta WordNet EBL bezala aurkezten den beti:

> *WordNet can best be characterized as somewhere in between a semantic network and a conceptual ontology. The synsets are conceptual units rather than lexical semantic units. The relations are better seen as semantic inferencing schemes than as lexicalization patterns.*

Beste konparazio lan batean, *Communications of the ACM* aldizkariaren 1995.eko azaroko alean, EDR, CYC eta WordNet bata bestearekin alderatzen dira, errepresentazio oinarri eta eduki kopuruen arabera. Aipatzen den diferentzia nabariena orientazioa da: CYC-ek sen ona eta munduari buruzko inferentziak jaso nahi dituen bitartean, EDR eta WordNet inferentzia linguistikoetarako daude prestatuta. Baina diferentzia hori ez da hain garrantzitsua, EAGLES-en barne txostenean aitortzen den bezala EuroWordNet-i buruz ari direnean:

> *EuroWordNet is different from AI-ontologies such as CYC or Sensus/Pangloss in that its focus is on the linguistically-motivated relations rather the semantic inference schemes only. In this respect it provides information on the exact semantic relation between the lexicalized words and the expressions of languages (this may still be useful for making inferences as well).*

Diferentzia nagusia orientazioan dagoela uste dugu guk ere: ontologiatan munduari buruzko informazioa dugu, kontzeptuen arteko erlazioak ez dute zertan motibazio linguistikorik eduki behar. Bestalde, EBLak hizkuntzaren ulermen eta sormenerako beharrei erantzutera mugatzen saiatzen dira, baina azken finean jakina da LNP *AI-complete* dela, hau da, adimen artifizialeko arazo garrantzitsuenak, sen ona barne, ebatzi behar direla LNP osoa egin ahal izateko. Beraz, EBLetan munduari buruzko informazioa egon behar da. Adibide garbi bat hiperonimia erlazioa da. Izan ere ontologietan eta EBLetan gordetzen den informazio semantikoa gainjarri egiten da, biak egitura isolatu bezala diseinatuko balira, ezagutza bera bi aldiz errepresentatu beharko litzateke, adibidez hiperonimiari dagokiona.

Tesi-lan honi dagokionez, kontzeptu/adieren arteko erlazio-izaera landu nahi dugunez, kontzeptu/adieren arteko erlazioak dira interesatzen zaizkigunak, bereziki klase/azpiklase edo

[17] "Preliminary Recommendations on Semantic Encoding" (Interim Report, May 1998). http://www.ilc.pi.cnr.it/EAGLES96/rep2/

hiperonimo/hiponimo. Erlazio horiek ontologia eta EBLetan topatu ditzakegunez (ontologiatan kontzeptuen arteko erlazio semantiko eta pragmatiko bezala, eta EBLetan adieren arteko erlazio lexikal-semantiko bezala) ez zaigu axolako beraien jatorria. Tesi honetan garatu dugun erlazio-izaera berdin aplikatu daiteke ontologia, EBL edo HEBetan azaltzen diren erlazioetara.

Tesi lan honetan ontologia eta EBL artean bereiziko ez dugun bezala, kontzeptu eta adiera inongo diferentziarik egin gabe erabiliko ditugu, nahiz eta jakin adiera lotuago dagoela hiztegi eta EBLetara, eta kontzeptua ontologietara.

II.C. Erabili ditugun baliabide lexikalak

WordNet da zalantzarik gabe tesi honetako baliabide oinarrizkoena, III. kapituluan definitzen dugun erlazio-izaera WordNet-eko erlazioen gainean inplementatu dugu eta. WordNet aukeratzeko arrazoiak beherago ikusiko ditugu. Corpusei dagokionez, hitzen adiera desanbiguazioan (ikus IV. kapitulua) lortutako emaitzak ebaluatzeko SemCor erabili dugu. Zuzenketa automatikoari buruzko ikerketan (V. kapitulua) Brown eta Bank of English.

VI. kapituluan HEB bat aberastuko dugu, *Le Plus Petit Larousse* hiztegitik erauzi izan dena, eta horretarako WordNet-era lotuko dugu *Oxford French/English Dictionary*-ren bitartez.

Ikusi dezagun arreta handiagoz zeintzuk diren baliabide hauen ezaugarriak.

II.C.1. Brown eta Semcor

Brown deritzon corpusak (Francis & Kucera, 1967) Estatu Batuetako ingeles idatziko 1.000.000 bat hitz jasotzen ditu. Idatzizko genero ezberdinetatik laginak jasoaz burutu izan da. Jasotako genero batzuen adibideak: *press-reportage*, *press-editorial*, *learned-science* eta *humour* dira.

Semcor Brown corpusaren azpimultzo bat da, WordNet egin zuen talde berak etiketa semantikoak gehitu dizkiona (Miller et al. 1993). Brown corpuseko 186 testu daude barnean, eta hitz guztietatik –359.732–, adjektibo, izen, aditz eta adberbioak daude WordNet-en dagokien adierarekin markatuta –192.639– (ikus 2. taula). Adieraz etiketatu daudenetik 666 hitzek jaso dute adiera bat baino gehiago, bi esanahirekin erabili direlakoan. Gainontzeko guztiak adiera bakarraz daude etiketatuta.

Hitz kopurua	359.732
Adieraz etiketatuta	192.639
Adiera anitzez etiketatuta	666

2. taula: Semcor-en datu batzuk

Corpus honetan horrela azaltzen da "*The couductor said to Ritchie:*" esaldia (WordNet 1.4 bertsioaren arabera etiketatuta):

```
<s>
<stn>50</stn>
<wd>The</wd><tag>DT</tag>
<wd>conductor</wd><sn>[noun.person.1]</sn><tag>NN</tag>
<wd>said</wd><mwd>say</mwd><msn>[verb.communication.0]</msn><tag>VBD</tag>
<wd>to</wd><tag>TO</tag>
<wd>Ritchie</wd><df>person</df><sn>[noun.Tops.0]</sn><pn>person</pn><tag>NP</tag>
<wd>:</wd><tag>:</tag>
</s>
```

Etiketak SGML formatua jarraitzen dute. Hitz-formak `<wd> </wd>` artean daude, kategoria sintaktikoa `<tag> </tag>` artean ematen da, eta etiketa semantiko `<sn> eta </sn>` artean. Adibidez *conductor* hitza izen bat da (NN) eta esaldi horretan `noun.person.1` bidez errepresentatzen den adiera dagokio, hau da, `person` kode semantikoa duen lehenbiziko adiera (WordNet ikustean komentatuko dugu zer diren kode semantiko horiek). Izen berezien kasuan etiketa semantikoa izen berezi horrek ordezkatzen duen entitatearen araberakoa da, adibidez *Ritchie*-ri pertsonaren adiera bat egokitu zaio. WordNet aipatzean ikusiko dugu etiketa semantikoen esanahia.

II.C.2. Bank of English

Collins hiztegigintzako konpainiaren COBUILD proiektuaren barnean[18], ingelesaren bilakaera monitorizatzeko corpusa da, Birmingham-eko Unibertsitatearen laguntzarekin jasotzen ari dena[19]. 1996.enean corpusak 320 miloi hitz zeuzkan eta hazten darrai egunotan ere. Brown corpusa ez bezala ezin da libreki eskuratu, eta baimena eskatu behar da corpusaren zatiak ikusi ahal izateko.

II.C.3. WordNet

WordNet (Miller et al. 1993b) da zalantzarik gabe tesi honetako baliabide oinarrizkoena. III. kapituluan definitzen dugun erlazio-izaera ontologietako erlazioetan oinarritzen da, eta eskuragarri dauden ontologien artean[20] hitz kopuru aberatsena duenez (126.520), WordNet hautatu dugu erlazio-izaeraren inplementazioa gauzatzeko. Beste hautagaiak Mikrokosmos eta Sensus ziren. Lehenbizikoak erlazio aberatsak dauzka kontzeptuen artean, baina lexikoa nahiko mugatua du (hitz kopururik ez dute aipatzen, baina bai 4.500 kontzeptu dituela). Bigarrena, hein handi batean, Mikrokosmos eta WordNet bat egitetik sortu zen. Hitz kopuru interesgarria dauka (90.000), baina

---

[18] http://titania.cobuild.collins.co.uk/

[19] http://titania.cobuild.collins.co.uk/boe_info.html

[20] Ontologia zabal gehienak lortu ahal izateko, CYC eta EDR kasu, gogotik ordaindu behar dira. MindeNet-en kasuan ezta ordaintzen ere ezin da eskuratu. Beste ontologia batzuk barne-erabilerarako dira, eta ez daude prestatuta kanpokoak erabiltzeko (adibidez, NounSense).

era automatikoan eraiki zenez erroreak daude hierarkian. Tamalez ez da errore horren neurririk ematen (Knight & Luk, 94). Azkenik, aipatu behar da WordNet oso erabilia dela LNP inguruko ikerkuntzan eta edozeinek eskuratu dezakeela Internet bidez[21].

WordNet Estatu Batuetako ingelesarentzat eraiki den EBLa da. Diseinatzeko orduan psikolinguistikako printzipioak aplikatu nahi izan dituzte. Kategoria nagusiek (izen, aditz, adjektibo eta adberbioak) sistema erlazional separatuak eratzen dituzte. Sistema erlazional horiek sinonimo multzoa (*synset*) daukate unitate kontzeptual bezala. Hitz batek adiera anitz baditu hainbat synsetetan azalduko da, eta adiera bakarra badu synset bakarrean. Adibidez *woman*-ek lau adiera dauzka, bakoitzean sinonimo ezberdinak dituelarik:

```
1. woman, adult female
2. womanhood, woman
3. charwoman, char, cleaning woman, cleaning lady, woman
4. woman ((informal) a female person who plays a significant role
```

4. adierak ez du sinonimorik, eta beraz glosa bat ere ematen du (glosa horiek beste adierentzat ere lortu daitezke.

Synset-en artean erlazio lexikal-kontzeptualak definitu dira (ikus 3. taula). Sinonimiaz gain, izenen kasuan garrantzitsuena hiperonimia da, hierarkia eratzen duena. Adibidez, *woman*-en lau adieren hiperonimoak hauek dira:

```
woman, adult female                        => female, female person
womanhood, woman       => class, social class, socio-economic class
charwoman, char, cleaning woman, cleaning lady, woman    => cleaner
woman                                      => female, female person
```

Bestelako erlazioen artean meronimia eta antonimia ere azaltzen dira, baina ez daude hain sistematikoki landuta. Izenen artekoa ez den erlazio bakarra *ezaugarri* erlazioa da, izen eta adjektibo bat lotzen baititu. Adibidez *canary*-ren ezaugarri bat *small* izatea da. Erlazio bakoitzak bere alderantzizkoa ere badu.

WordNet-en 1.5 bertsiorako izenen datuak 3. taulan ikus daitezke. Izenek batez-beste 1,22 adiera dauzkate[22]. Erlazioei dagokienez gehienak hiperonimia eta hiponimia erlazioak dira, eta synset

[21] http://www.cogsci.princeton.edu/~wn

[22] Kontuan izan synset bat hitz bat baina gehiagoren adiera izan daitekeela, beraz 1,22 ez da izen eta synset kopuruaren arteko zatiketa soila.

bakoitzak bana dauka batez-beste. Meronimia edo holonimia erlazioak synset-en erdiak dauzkate, eta gainontzeko erlazioak askoz gutxiago azaltzen zaizkigu.

		Kopurua	Izeneko	Synset-eko
Izenak		87.671		
Synset-ak		60.631	1,22	
Erlazioak	Hiperonimia/hiponimia	122.246		2,01
	Meronimia/holonimia	35.067		0,58
	Antonimia	1.713		0,03
	Ezaugarriak	645		0,01
	Guztira	159.670		2,63

3. taula: WordNet 1.5-eko datu batzuk izenentzat

Informazio honetaz gain WordNet-eko izenen synsetak 26 eremu semantikotan sailkatuta daude. Eremu horiek 4. taulan daude. WordNet-en izen baten adiera zuzenean adieraz daiteke, edo zeharka, eremu semantiko horren arabera. Adibidez *conductor* izenaren synset bat, garraio publikoan kobratzen duen pertsonari dagokiona[23], *person* eremu semantikoari dagokio. Synset hori bi eratara adieraz daiteke, bere 3. adiera bezala, edo `[noun.person.1]` bezala, hau da, *person* eremu semantikoan *conductor*-ek duen lehenbiziko adiera bezala[24]. Eremu semantikoen artean noun.Tops berezia da, hierarkien goialdean dauden synset-ak bildu besterik ez du egiten eta.

noun.Tops	noun.feeling	noun.possession
noun.act	noun.food	noun.process
noun.animal	noun.group	noun.quantity
noun.artifact	noun.location	noun.relation
noun.attribute	noun.motive	noun.shape
noun.body	noun.object	noun.state
noun.cognition	noun.person	noun.substance
noun.communication	noun.phenomenon	noun.time
noun.event	noun.plant	

4. taula: WordNet-eko izenen kode semantikoak

II.C.4. LPPL

Le Plus Petit Larousse (Larousse, 1980) frantseseko hiztegi elebakarra da. 5. taulan ikus daitezke hiztegiaren datuak. Hiztegi honen gainean ikerkuntza ugari egin ditu gure taldeak. Lehenbizi Datu-Base Lexikal bat eratu zen hiztegiko informazio guztiarekin: sarrera, adiera zenbaki, kategoria, erabileremu, definizio eta adibide. Definizioen gainean egindako analisi sintaktikotik hainbat erlazio lexikal-semantiko erauzi ziren. Izenen kasuan honako erlazio hauek erauzi ziren: sinonimia eta antonimia, hiperonimia, meronimia, gabezia, erreferentziazkoa, eratorpena eta kasu-erlazioak.

[23] Synset hori horrela adierazten da WordNet-eko interfazean: *conductor -- (the person who collects fares on a public conveyance)*

[24] Eremu semantiko berdineko beste adieraren synseta: *conductor, music director, director1 -- (the person who leads a musical group)*

	Guztira	izenak
Sarrerak	15.953	10.506
Adierak	22.899	13.740
Hiztegiko hitzak (guztira)	97.778	66.323
Definizioen luzera (batez-beste)	3,27	3,82

5. taula: LPPL-ko datuak

Erlazio lexikal-kontzeptual horiekin Hiztegi-Ezagutza Base bat eratu zen, sare semantiko baten itxura zuena.

II.C.5. OFED

Oxford French-English Dictionary (OUP, 1989) neurri ertaineko hiztegi elebiduna da. Hiztegi honen frantses-ingeles zatia bakarrik dugu makinak irakurtzeko formatuan. Hiztegiari buruzko datuak 6. taulan ikus ditzakegu. Hiztegiak izenentzat 13.030 sarrera dauzka. Sarrera bakoitzak jatorrizko hitzarentzat adiera bakarra edo gehiago eduki ditzake. Halako adiera elebidun bakoitzari azpisarrera deituko diogu lan honetan. Adibidez *maintien* izenaren sarrera bi azpisarreratan bana daiteke:

maintien n.m. (attitude) bearing; (conservation) maintenance

maintien 1: n.m. (attitude) bearing
maintien 2: n.m. (conservation) maintenance

Hiztegi elebidunak 16.917 halako azpisarrera dauzka izenentzat. Beste ikuspegi batetik ikusita, 13.030 izen frantses eta 11.969 izen ingeles daude hiztegian (ikus 6. taula).

	Sarrera kop.	Azpisarrera kop.
Guztira	21.322	31.502
Izenak	13.030	16.917
Ingeles izenak	11.969	–

6. taula: OFED hiztegi elebiduneko datuak

Azpisarreren barruan hainbat eremu azaldu daitezke: kategoria (derrigorrez, adibidez izen maskulinoa, *n.m.*), eremu semantikoa (aukerakoa, 20 eremutako bat izan daiteke, adibidez beheragoko adibideko *comm.*, komertziala), frantsesez dagoen argibidea (aukerakoa, adibidez goiko *attitude* eta *conservtion*, edo beheko *ressources*), eta azkenik derrigorrezkoa den ingelesezko itzulpen-hitza edo hitz-zerrenda. Eremu semantikoa eta frantsesezko argibidea azpisarrera horretako itzulpenaren argibideak dira, testuinguru edo erabilpenari buruzko oharrak, hiztegiaren erabiltzaileari itzulpena hautatzean laguntzeko.

folie 1: n.f. madness
provision 1: n.f. supply, store
trésor 2: n.m (ressources) (comm.) finances

III. Kapitulua
ERLAZIO-IZAERA ETA DENTSITATE KONTZEPTUALA

Kapitulu honen helburu nagusia ezagutzan oinarritutako kontzeptuen arteko erlazio-izaera definitzea da, eta horretarako WordNet-en oinarritutako Dentsitate Kontzeptuala diseinatu eta inplementatu dugu. Lehenbizi erlazio-izaera zer den azalduko dugu, eta literaturan azaldu diren lan garrantzitsuenak gainbegiratuko ditugu, lan bakoitzak erabili izan duen baliabide lexikalaren arabera sailkatuta. Hurrengo atalean, ontologiatan oinarritzen den Dentsitate Kontzeptuala azalduko dugu, bere aurrekaria den Distantzia Kontzeptualarekin batera. Ondoren WordNet-erako egin dugun inplementazioa agertzen da. III.D. atalean Dentsitate Kontzeptualaren ezaugarrien ebaluazioa egin, eta gainontzeko proposamenekin alderatuko dugu. Bukatzeko, kapitulu honen ekarpen nagusiak eta etorkizunerako lana labur aipatuko ditugu.

III.A. Sarrera eta aurrekariak

Kapitulu honen helburuan sakondu aurretik, lan honetan erabiliko dugun terminologia finkatuko dugu, antzekotasunaren literaturan gertatzen den nahastea argitu nahian. Bi ideia nagusi dira ardatz, maiz nahasten direnak: **antzekotasuna** (ingelesezko *similarity*) eta **erlazio-izaera** (*relatedness*). Lehenbizikoa bi objektuk elkarren antza dutela adierazteko erabiltzen da, adibidez goilare eta sardexka. Bigarrena bi objektu horien artean nolabaiteko erlazioa (lotura, harremana) badagoela esateko, adibidez sardexka eta txuleta artekoa. Antzekoak diren bi gauza erlazionatuta egongo dira (adibideko goilare eta sardexka), noski, baina alderantziz ez da gertatzen: erlazionatutako bi gauzek ez daukate zertan antzeko izan behar (adibideko sardexka eta txuleta). Literaturan antzekotasun hitza da zabalduena, sarritan erlazio-izaera beharko lukeen tokian erabilia. Gure ustez orokorrean erlazio-izaeraz hitz egin daiteke, eta antzekotasuna azpimultzo bat izango litzateke. Antzekotasun eta erlazio-izaerari ontologien inguruko lan batzuetan **distantzia semantikoa** (*semantic distance*) kontrajarri ohi zaio: antzekotasun handiko bi kontzepturen artean distantzia semantiko txikia egongo litzateke. Antzekotasuna eta distantzia semantikoa bata bestearen alderantzizkoa dira, eta beraz distantzia semantikoa definitzea ez da beharrezkoa. Tesi honetan, hala ere, distantzia semantikoa ez baina **distantzia kontzeptuala** erlazio-izaeraren neurri eta inplementazio konkretu bezala bai azalduko zaigula.

Kontua da erlazio-izaera hori askoren ustetan lengoaia naturala ulertzeko giltzetako bat dela. Ulermenerako giltza edo ez, LNParen aplikazio konkretu askotan erabiltzen da erlazio-izaeraren inplementazioren bat edo beste: zuzenketa automatikoan (ikus V. kapitulua), informazioaren berreskuratzean (*Information Retrieval*), dokumentuen berreskuratze eta sailkapenean (*Document indexing and retrieval*) (Sussna, 1993), multzokatzean (*clustering*) (Schütze 1992a; 1992b), desanbiguazioan (anbiguetate sintaktikoan –adibidez, ingelesezko *prepositional phrase attachment* arazoan (Resnik, 1993)– edo hitzen adiera-desanbiguazioan, ikus IV. kapitulua), ontologien eraikuntzan (taxonomiak eraikitzean –ikus VI.A atala– , hautapen-murrizpenak ikastean (Grishman & Sterling, 1994), ontologiak biltzean (Knight & Luk, 1994; Utiyama & Hasida, 1997), edo ontologien ebaluazioan (Rada et al., 1989)) eta baita ere interpretazio semantikoan (EDR, 1993).

Arrazoi honengatik erlazio-izaerari buruzko literatura zabala da. Artikulu gutxi batzuetan bera da helburua edo aipatu egiten da, baina artikulu asko aplikazio konkretu bati buruzkoak dira eta ez da erlazio-izaerari buruz esplizituki hitz egiten, nahiz eta inplizituki erlazio-izaeraren neurriren bat definitu. Gai honen inguruko literatura aztertzean tesian aipatuko ditugun artikulu ugari azalduko zaizkigu, nola edo hala erlazio-izaeraren neurriren bat erabiltzen dute eta.

Artikulu eta lanak sailkatzea ez da makaleko lana, bai kopurua bera itzela delako, bai hurbilpen oso ezberdinak daudelako. Nolabait esateko badirudi ikertalde bakoitzak bere erlazio-izaeraren formalizazioa bilatu duela. Formula guztiek dauzkate ahuleziak eta aldeko ezaugarriak, alor hau heldutasunera heldu ez denaren seinale, ziur aski. Baina ulergarria da, bestalde, kontuan hartzen badugu aplikazio askotarako beharrezkoa izanda, ikertalde bakoitzak abiapuntu ezberdinetik heldu diola erlazio-izaerari. Denak sakonean aztertzea, beraz, tesi lan honen helburutik kanpo dago, baina bai arrakastatsuenak eta lan honetatik hurbilago daudenak sailkatu eta aztertzen saiatuko garela. Sailkapena egituratzeko irizpide nagusi bat erabili dugu, erabilitako baliabidearena: ontologia, hiztegi elektronikoa, corpusa edo horien konbinazioren bat.

Beste kontzeptu batzuk ere erabiliko ditugu lanak sailkatu ahal izateko. Hasteko, hurrengo bereizketa egingo dugu bi hitz edo bi kontzepturen arteko erlazioen inguruan:

1. **Erlazio paradigmatikoa**: linguistikoki, esaldi batean hitz bat beste baten ordez trukatu daitekeenean. Kontzeptualki, munduaren ontologia jakin baten arabera, mota berdineko kontzeptuak direnean. Hau da antzekotasun bezala ulertu daitekeena, antzeko kontzeptuak klase berean egoten baitira sailkatuta.
2. **Erlazio sintagmatikoa**: linguistikoki, bi hitz kate mintzatu berean azaltzen direnean. Koordenatu pare batez esan daiteke erlazio paradigmatikoa bertikala baldin bada, sintagmatikoa horizontala dela (UZEI, 1982). Kontzeptualki, mota ezberdineko kontzeptuak izanda ere horien artean erlazioa dagoenean. Hau da berez erlazio-izaera. Testuinguruari dagokionez are gehiago bereizi ohi dira:
    - **Erlazio sintagmatiko lokala**: kolokazioak dira honen adibide bat, adibidez 'on egin', edo argumentu egituran azaltzen dena, adibidez 'urdaiazpikoa jan'. Halakoetan bi hitzak esaldian gertu egon ohi dira, gutxi gora behera.

    - **Erlazio sintagmatiko globala**: erlazionatutako hitzak ez dira zertan hurbil azaldu behar, ezta esaldi berean ere. Topiko edo mintzagaiarekin lotutako erlazioak azaltzen zaizkigu hemen: adibidez sukaldaritza balizko topikoari lotutako urdaiazpiko, lapiko, sardexka, sukalde, etab. Mintzagaiak erlazionatzen dituela esan daiteke beraz.

      Kasu batzuetan ez da eskatzen bi hitzak kate mintzatu berean azaltzea, baizik eta ezaugarri (sintaktiko edo semantiko) amankomuneko kate mintzatuetan. Honela, bi hitz antzeko testuinguruetan maiz azaltzen badira, beraien artean **zeharkako erlazio sintagmatiko globala** dagoela esan daiteke.

Bereizketak lauso samarra iruditu arren, aurrerago ikusiko dugu lan praktiko ugaritan ondo nabarituko dela bata edo bestearen erabilera, formalizazio bakoitzak aukeratu duen hurbilpenaren arabera.

Beste bereizketa bat hitzen arteko erlazio-izaera eta kontzeptuen arteko erlazio-izaera bereizten dituena da. Bigarrena da gehien interesatzen zaiguna, hau da, erlazio linguistikoa baino kontzeptuala. Adieraren garrantziaz jabetzeko zera dio Hirst-ek (1987: 5 or.): "*Any practical NLU system must be able to disambiguate words with multiple meanings, and the method used to do this must necessarily work with the methods of semantic interpretation and knowledge representation used in the system*". Ontologia eta Hiztegi Ezagutza Baseak (HEB) ere kontzeptuen inguruan antolatu ohi dira, adibidez WordNet-en: "*The most ambitious feature of WordNet, however, is its attempt to organize lexical information in terms of word meanings, rather than word forms*" (Miller et al., 1993b: Sarrerako 3 or.). HEB eta EBLetan badaude salbuespenak, sistema batzuetan ezin izan baitute adiera-desanbiguazioa aurrera eraman, baina adieraren inguruan antolatu beharra aitortzen dute, Richardson kasu (1997: 113 or.): "*In the future, this approach may be much more viable with a sense disambiguated Lexical Knowledge Base, which is work currently in progress.*".

Hitzen edo adieren artekoa izanda ere, bi erlazio-izaerak hertsiki erlazionatuta daude. Linguistikoki antzekoak diren hitzak, beraien adieraren batean kontzeptualki antzekoak ere izango dira, eta alderantziz, antzekoak diren bi kontzepturentzat ahoskatzeko balio duten hitzak ere antzekoak izango dira.

Orain artekoa kontuan izanik, erlazio-izaerari buruzko lanen azterketan sei ezaugarriri egingo diegu arreta berezia:

- erabiltzen den baliabidearen ingurukoa: hiztegi, ontologia, corpus edo nahasketa.
- erlazio-izaera paradigmatiko edo sintagmatikoa (global/lokala) den.
- hitz edo kontzeptuen arteko erlazio-izaera den.
- testu zabalekin ebaluatua, hitz gutxi batzuekin ebaluatua edo ebaluatu gabeko proposamena den.
- izenekin soilik ebaluatua edo kategoria guztiekin ebaluatuta dagoen.
- lortutako emaitzak: emaitzarik ez, kaxkarrak, onak edo oso onak, azaldutako doitasunaren arabera.

Esan dugun bezala, erlazio-izaeraren formalizazioen ebaluazioa ez da erraza. Batzuetan zuzenean pertsonen iritziz *ad hoc* osatutako zerrendekin parekatuaz egiten da, baina gehienetan adiera-desanbiguazioan, informazioaren berreskuratzean edo beste aplikazio espezifiko batean lortutako emaitzen bidez zeharka egiten da. Lehenbizikoak duen arazoa zera da, pertsona ezberdinek osatzen dituzten zerrendak ez direla guztiz bat etortzen, eta zerrenda eraikitzeko irizpide garbirik ez dagoela. Erlazio-izaera erabiliaz automatikoki eraikitako zerrendak pertsonek eraikitakoekin parekatzean, zerrendak antzekoak badira orduan formalizazioa ontzat hartzen da, baina ez da kontuan hartzen bat ez datozen hitzak zerikusirik duten edo guztiz erratuak dauden.

Aurrekarien azterketari ekingo digu orain. Goian aipatutako ezaugarrietan arreta berezia jarriko dugunez, sistema edo lan esanguratsuenak komentatu ondoren lerro batean laburbilduko dugu ezaugarri bakoitza zertan den lan konkretu horrentzat.

III.A.1. Ontologian oinarritutako aurrekariak

Ontologia (ikus II. kapituluan zer den ontologia lan honi dagokionean) oinarritzat hartuz gero, bi objekturen arteko erlazio-izaera ontologia bertan dagoen informaziotik erauzi daiteke. Psikologiaren eremutik sortu zen antzekotasunaren lehenbiziko axiomatizazioan Tversky-k (1977) zera zioen: "*A new set-theoretical approach to similarity is developed in which objects are represented as collections of features, and similarity is described as a feature-matching process*". Ezaugarrietan oinarritutako errepresentazio eredua erabiltzen zuen beraz. Bere neurria zeregin ezberdinetara aplikatzen du, hala nola, hizkien antzekotasuna, aurpegien antzekotasuna eta nazioen antzekotasuna. Ebaluazioan bere axiomatizazioa antzekotasunari buruzko giza iritziarekin alderatu zuen.

Adimen Artifizialean ordea, garai horretan sare semantikoak ziren errepresentazio eredu ohikoenak, eta antzekotasuna batez ere *spreading activation* izeneko tekniken bidez landu zen (Quillian, 1968; Collins & Loftus, 1975). Collins eta Loftus-en arabera "*The conceptual network is organized along the lines of semantic similarity. The more properties two concepts have in common, the more links there are between the two nodes via these properties and the more closely related are the conccepts*"[25]. Ez zuten beraien eredua zuzenean inplementatu, baina psikolinguistikako esperimentuen araberako datuekin bat omen zetorren.

Spreading activation horren inplementazioa errazte aldera, Rada-ren taldeak (Rada et al., 1989) lan ugari egin zituen sare semantikoen ebaluazio eta fusionatzearen inguruan. Beraiek aurkezten duten erlazio-izaeraren neurriari Distantzia Semantikoa (*Semantic Distance*) deritzo:"… *[in spreading activation] semantic relatedness is based on an aggregate of the interconnections between the concepts. This is different from semantic distance which is equal to the minimal path length between two concepts*". Are gehiago, kontuan hartuaz sare semantikoak egituratzen dituen erlazio pribilegiatu bat egon badagoela – klase-azpiklase edo *is-a* erlazioa – erlazio mota guztiak erabili ordez azpiklase erlazioa nahikoa dela diote: "*we hypohesize that […] is strong enough for the length of is-a paths to be used as a measure of semantic relatedness*". Proposatzen duen distantziaren formulan (1. ekuazioa) A eta B kontzeptuen arteko distantzia bi kontzeptuen arteko *is-a*[26] erlazioz osatutako bide motzenaren luzera da.

$$\mathrm{dist}(A,B) = \min_{p \in \mathrm{path}(A,B)} \mathrm{length}(p) \qquad (1)$$

[25] Ikusten den bezala antzekotasun eta erlazio-izaera kontzeptuak nahastu egiten dira hemen ere.

[26] Tesi honetarako beharrezkoa ez denez, ez dugu ezberdinduko *is-a*, klase/azpiklase edo hiperonimo/hiponimo erlazioen artean.

Distantziaren neurria txikia litzateke hertsiki erlazionatutako bi kontzepturentzat, eta alderantziz. Ez dute ebaluaziorik adierazi. Bere sinpletasunean nahikoa erabili izan da, adibidez ontologia ezberdinak biltzeko (Knight & Luk, 1994; Utiyama & Hasida, 1997).

[27]*Ontologia/paradigmatikoa/kontzeptuak/gutxi/izenak/emaitzarik ez*

Sussna-k (1993) Rada-ren taldearen ideia landu eta WordNet ezagutza-baseari aplikatzen dio, dokumentuak indexatzeko adiera-desanbiguazioa beharrezkoa dela eta. Ezagutza-baseko kontzeptuak adierak dira kasu honetan, eta azpiklase erlazioaz gain WordNet-ek dauzkan beste guztiak ere erabiltzea proposatzen du. Erlazio bakoitzak antzekotasun pisu bat edukiko du (2. ekuazioko[28] $w_r(x,y)$), antzekoagoak baitira adibidez sinonimo-erlazio bidez lotutako kontzeptuak, zati (*part-of*) erlazioaz lotutakoak baino (ikusi baita ere Tversky 1977). Sare semantikoan elkarren ondoan dauden bi kontzepturen arteko distantzia ($w(x,y)$ 2. ekuazioan) bi kontzeptu horien artean dagoen erlazio guztien pisuen batura izango da. Aipatzekoa da, gero eta sakonago egon kontzeptuak hierarkian gero eta distantzia txikiagoa aitortzen diela (hori da d zatitzailea).

$$w(x,y) = \sum_{r \in Wordnet-relation} \frac{w_r(x,y)}{d} \qquad (2)$$

Edozein bi kontzepturen arteko distantzia, beraz, lotzen dituztenen bide guztien artean pisu txikiena duenak emango digu (3. ekuazioa).

$$\begin{aligned} &\text{dist}(x,y) = \min_{(x,x_1,\ldots,x_n,y)\in \text{path}(x,y)} \sum_{i=0}^{n} w(x_i, x_{i+1}) \\ &\text{non } x = x_0 \text{ eta } y = x_{n+1} \end{aligned} \qquad (3)$$

Sussna-k ere ez du ebaluazio zuzenik egiten, zeharka adiera-desanbiguazio esperimentuetan lortutako emaitzen arabera baizik.

Ontologia/paradigmatikoa/kontzeptuak/zabala/izenak/emaitza onak

Mahesh-ek eta (Mahesh et al., 1996; 1997) Mikrokosmos ontologia abiapuntu bezala hartu eta adiera-desanbiguazio lan baterako *spreading activation* itsu mutuan aritzen dela diote: " … *spreading activation … does not make use of available knowledge*." Beraien planteamenduan esaldiaren analisi

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[27] Hauek dira lehen aipatutako ezaugarrien balioak Radaren taldearen lanarentzat.

[28] Sussna-ren laneko w_r hemen azaltzen dena baino konplexuagoa da, baina berak aitortzen duen bezala "*the particular weights used* [w_r] *may not make that much difference*".

semantikoan ateratako argumentu-egitura errespetatu egin behar da adieren arteko bideak bilatzean. Beste modu batetara ikusita erlazio-izaerak aditz edo adjektiboaren hautapen-murrizpenei hoberen egokitzea neurtzen du, hautapen-murrizpen kontzeptualak ontologian errepresentatuaz, eta kontzeptuen arteko hurbiltasun paradigmatikoa ere erabiliaz. Mikrokosmos-en estaldura urria dela eta, ez dute aurkezten ebaluaziorik.

Ontologia/paradigmatikoa eta sintagmatiko lokala/kontzeptuak/proposamena/ izen-aditz/emaitzarik ez

III.A.2. *Hiztegi elektronikoetan oinarritutako neurriak*

Hiztegietan ez dago kontzepturik, adierak dira azaltzen direnak. Adiera horiek hala ere lexikografoak egindako kontzeptualizazioei erantzuten diete, eta hein handi batean ontologia bateko kontzeptuekin parekatu daitezke. Nola neurtu adiera horien arteko erlazio-izaera? Ontologia lanetan ez bezala, hemen ez dago psikologia edo ezagutzan oinarritutako formalizaziorik, praktikoak diren hurbilpenak baizik.

Erlazio-izaera motari buruz, hemen zeharkako erlazio sintagmatiko globalak erabiltzen direla esan dezakegu. Bi adiera lotuta dauden jakiteko adierak azaltzen diren testuingurua aztertzen da (hiztegiaren kasuan adieraren definizioa bera), eta testuinguru horiek antzekoak badira orduan adierak erlazionatuta egongo dira. Atzean dagoen hipotesia zera da, erlazionatutako adierak hitz antzekoez definitu izango direla.

Lesk-ek (1986) adiera-desanbiguaziorako aplikazioan zuzenean aplikatu zuen hipotesi hori: bi adieren arteko erlazio-izaeraren neurria beraien definizioetan agertzen diren amankomuneko hitzen kopurua da. Zenbat eta hitz gehiago egon bi definizioetan, hainbat eta estuago erlazionatuta egongo dira bi adierak. Bere intuizioa emankorra izan da orain ikusiko dugun bezala, baina bere horretan ahula da oso, definizioa idaztean hautatutako hitzen menpe baitago. Metodo honen ebaluazioa adiera desanbiguazio lan baten bidez egiten du. Cowie-ren taldeak (Cowie et al., 1992; Wilks et al., 1996) metodo bera proposatzen du, baina kontzeptu multzo zabalen arteko erlazio-izaera neurtzean eraginkortasuna hobetzeko *simulated annealing* delakoa erabiliaz.

Hiztegi/sintagmatiko globala/kontzeptuak/zabala/ izenak/emaitza kaxkarrak

Véronis eta Ide-k (1990) hurbilpen berari heltzen diote, baina hedatu egiten dute definizio zirkular bat erabiliz. Bi adieren arteko erlazioaren neurria definitzeko erabili diren hitzen arteko erlazioaren neurrien baturak emango du. Hau da, orain ez da beharrezkoa hitz berak agertzea bi adieren definizioan, nahikoa da erlazionatutako hitzak erabiltzea. Eta noiz daude bi hitz erlazionatuta? Beraien adierak erlazionatuta daudenean. Hipotesi hau eraginkorra den edo ez frogatzeko sare neuronal erraldoi bat eraiki zuten hiztegiko definizioetako hitzak erabiliz, definiendum eta definizioko hitzen arteko loturak gehituz[29], eta adiera-desanbiguazio lan batean probatu zuten (ebaluazio sistematikorik ez dute). Hurbilpen antzekoa darabilte Kozima eta Furugorik ere (1993), baina eraginkortasun-arazoak konpontzeko kasu honetan bektore-eredu batera itzultzen dute informazioa (Kozima & Ito, 1995), orain ikusiko dugun eredura (ikusi (Niwa & Nitta, 1994) ere). Hauek ebaluazioa pertsonen iritziz eraikitako antzekotasun-zerrendekin parekatuaz egiten dute.

Hiztegi/sintagmatiko globala/hitzak/gutxi/izenak/emaitzarik ez

Lesk-en metodoak beste hedapen bat jaso zuen, hiztegietako definizioetako agerkidetzez osatutako bektore-ereduekin. Wilks-ek eta (Wilks et al., 1990; 1996) LDOCE hiztegitik (ikus II.A.2 atala) hitzen agerkidetzak jaso zituzten. LDOCE-k murriztutako hiztegi bat (2781 hitz dituena) erabiltzen du definizioak idazteko, eta beraz agerkidetzak murriztutako hitz horietara mugatzen dira. Lan horien arabera bi hitzen arteko agerkidetza definizio berean azaltzen direnean ematen da. Hitz bakoitzaren agerkidetzak kodetzeko bektore bat erabiltzen dute (4. formulako $\vec{v}_w$). Bektore horretan hiztegi murriztuko hitz bakoitzeko (4. ekuazioko N da hiztegi murriztu horren tamaina) balio bat egongo da (v_i^w), hitzen arteko agerkidetzaren indarra errepresentatzen duena. Horretarako sei formula ezberdin proposatzen dituzte, denak hitzen eta agerkidetzaren maiztasunetan oinarritutakoak. 5. ekuazioan, adibidez, bektoreko balio bezala agerkidetzaren maiztasun gordinak azaltzen dira, hau da, w eta z_i hitzak elkarrekin agertzen direneko maiztasuna.

$$\vec{v}_w = \left(v_0^w, \cdots, v_N^w\right) \tag{4}$$

$$v_i^w = f_{w,z_i} \tag{5}$$

Bi hitzen arteko erlazio-izaera kalkulatzeko bektore horien arteko erlazioa matematikoki kalkulatu daiteke, adibidez angeluaren kosinua erabiliaz (ikusi 6. ekuazioa, baina beste hiru formula ere proposatzen dituzte). Wilks eta harantzago doaz ordea, eta adieren arteko erlazio-izaeraren neurria eduki ahal izateko, hiztegiko adiera bakoitzarentzat bektore bat eratzen dute bere definizioan agertzen diren hitzen bektoreak batuaz (7. ekuazioa). Horrela bi bektoreren arteko erlazioaren neurri matematikoak bi adieren arteko erlazio-izaera ematen digu (nahikoa da 6. ekuazioan w eta z hitzak baino adierak izatea, 7. ekuazioko bektorez errepresentatuak).

[29] Definizioak ez zeuden lematizatuta, ezta analizatuta ere.

$$\mathrm{sim}(w, z) = \cos(\vec{v}_w, \vec{v}_z) = \frac{\sum_{k=1}^{N}(v_k^a v_k^b)}{\sqrt{\sum_{k=1}^{N} v_k^a \sum_{k=1}^{N} v_k^b}} \tag{6}$$

$$\vec{v}_a = \sum_{w \in \mathrm{def}(a)} \vec{v}_w \tag{7}$$

Metodo honek definizioetako hitzen gainjartzea zuzenean neurtu ordez, hitz horien bektoreak erabiltzen ditu beraz. Ebaluazioa ez da oso sakona, *bank* hitzaren agerpen batzuk soilik desanbiguatuaz egin zuten eta.

Hiztegi/ sintagmatiko globala/ kontzeptuak/ gutxi/ izenak/ emaitza onak

Richardson-ek (1997) hartzen duen hurbilpenak ontologiakoentzat ikusitakoen antza dauka. Izan ere bi hiztegitako (*LDOCE* eta *W7*, ikus II.A.2 atala) definizioak sintaktikoki analizatu eta erlazio semantikoak erauzten ditu, sare semantiko bat eraikiaz. Erlazio bakoitzak maiztasunetan oinarritutako pisu bat du. Sare semantiko honetan definizioetako hitzak desanbiguatu gabe daudenez ezinezkoa zaio bi adieren arteko erlazio-izaera neurtzea. Horren ordez hitzen arteko erlazio-izaera lantzen du, baina bi hitz lotzen dituen bidean errorea egon daitekeenez (adiera ezberdinekoak balira tarteko hitzak) oso bide motzak erabiltzen ditu, gehienez bi definiziotako hitzak erabili ahal direlarik. Ideia beraz zera da, bi hitz hertsiki erlazionatuta egongo dira beraien artean erlazio-bide asko badaude. Erlazio-bide guztiak ez dira esanguratsuak ordea, eta erlazio-bide mota bakoitzaren erabilgarritasuna neurtzeko beharrean aurkitzen da. Hori egiteko metodo enpiriko bat erabiltzen du, thesaurus bateko 50.000 hitz pare eta erlaziorik ez duten beste 50.000 hitz pare erabiliz. Ebaluazioa thesaurus hori bera erabiliz egiten du, pisu horiek kalkulatzeko hitzak kontuan hartu gabe, noski.

Hiztegi/ paradigmatikoa eta sintagmatiko globala/ hitzak/ zabal/ izenak/ emaitza onak

III.A.3. Corpusetan oinarritutako alternatibak

Corpusen erabilera bultzatzen dutenak maiz aipatzen dute "*you shall know a word for the company it keeps*" (Firth, 1957), hau da, hitzen ezaugarri eta esanahia hitz hori azaltzen den testuinguruak emango du, edo hobeto esanda, azaldu izan den testuinguru guztien analisiak. Horretan oinarrituta, honako hipotesia zabaldu da: bi hitz hertsiki erlazionatuta egongo dira antzeko testuinguruetan azaltzen badira. Hitzen arteko erlazio-izaera aztertzeko, hitz horiek azaltzen diren testuinguruak konparatzea besterik ez da behar. Erlazio sintagmatiko global eta lokala kontuan hartuko diren edo ez testuinguruaren definizioaren arabera egongo da: erlazio sintagmatiko lokala aztertu nahi bada, erlazio sintaktiko zuzena duten hitzak erabiliko dira. Erlazio sintagmatiko globalaren kasuan leiho zabalak definitzen dira, ±50 hitzetakoak, baina ordena kontuan hartu gabe eta izen, adjektibo eta aditzetaz soilik baliatuaz.

Corpusean oinarritzen diren teknikak adieren arteko erlazioetara hedatu ahal izateko corpuseko hitzak beraien adieraz etiketatu behar dira, entrenamendu-corpus bat eratuaz. Hau da hain zuzen ere corpusetan oinarritutako tekniken arazo bat, eskuzko desanbiguazio zabal baten beharra.

Neurri sinple eta arrakastatsuenetako bat informazioaren teorian oinarritutako Elkarren Arteko Informazioa da (EAI, *mutual information*, Church & Hanks, 1990; Gale et al. 1992; 1993). Horren arabera beti elkarrekin azaltzen badira bi hitzen arteko erlazio-izaera indartsua izango da, eta ahula, aldiz, ez direnean inoiz testuinguru berean azaltzen. Church eta Hanks-en arabera, testuingurua hitzen agerpenaren inguruan dauden 100 hitzetako leihoak erabiltzen dira. Horrela v eta w hitzen EAI kalkulatzeko hitz bakoitza agertzeko eta biak batera agertzeko probabilitateak eduki behar dira kontuan (8. ekuazioa).

$$\mathrm{EAI}(v, w) = \log \frac{\Pr(v, w)}{\Pr(v)\Pr(w)} \tag{8}$$

Probabilitate horiek estimatzeko modu errazena agerpenak kontatu (ikusi f 9. ekuazioan) eta N hitz kopuru totalaz zatitzea da (aukera gehienezko estimazioa – *maximum likelihood estimate* – deritzon teknika).

$$\Pr(x) \cong \frac{f_x}{N} \tag{9}$$

Corpus/ sintagmatiko globala/ hitzak[30] */gutxi/ izenak/ emaitza onak/ datu urrien arazoa*[31]

EAI aplikazio askotan erabili izan da, eta beraren inguruko literaturan gehien aipatzen den arazoa estimazioarena da. Gainontzeko teknika estatistikoek ere arazo honi aurre egin beharko diote, izan ere, hitz gutxi batzuk oso maiz azaltzen dira testuetan, baina hitz gehienak oso-oso urritan (Zipf-en legearen arabera). Horregatik deitzen zaio arazo honi datu urrien arazoa (*sparse data problem*). Zein da inoiz ikusi gabeko hitz bat azaltzeko probabilitatea? Edo corpus osoan birritan azaldu diren bi hitz

[30] Hitzen arteko erlazio-izaera bezala jartzen dugu, adieratara hedatzea ez delako naturala, eskuzko etiketatzea beharko lukeelako.

[31] Corpusetan oinarritutako alternatibetan garrantzitsua denez, datu urrien arazoei buruzko iruzkinak gehitu dizkiegu beste ezaugarrieri.

batera aurkitzeko probabilitatea elkarrekin azaldu ez direnean? Garbi dago ez dela 0. Honi aurre egiteko teknikei leuntze-teknika (*smoothing*) deritze.

Schütze-ek (1992a; 1992b; 1998) hitzen arteko gertakidetzak kontuan hartzeko beste modu bat erabili zuen, bektore bezala kodetu eta bektoreen arteko angelua erabili hitzen gertutasuna neurtzeko (ikus Wilks-en metodoa aurreko III.A.2. atalean). Adieren arteko erlazio-izaerara hedatu ahal izateko, hitz baten testuinguruak multzokatu egiten ditu, horretarako testuinguruko bektore guztiak batu eta multzokatze teknika aplikatuz. Horrela hitz jakin baten agerpenak giza-aditu batek adieren arabera sailkatu ditzake, testuinguru jakin batzuei adiera bat esleituz. Corpus osoko hitzaren agerpenak banan-banan etiketatzea baino ahalegin gutxiago beharko litzateke, autorearen arabera.

Corpus/ sintagmatiko globala eta lokala/ hitzak/ zabal/ izenak/ emaitza onak/ datu urrien arazorik ez

EAIak eta Schütze-ren bektoreek testuingurutik hitzen agerpena besterik ez dute kontuan hartzen, baina bada gehiagorik, egitura sintaktikoa esate baterako. Era sinpleenean hitzaren aldamenean dauden hitzen kategoriak hartu daitezke kontuan, baina egitura landuagoan argumentu egiturak (aditz-objektu, izen-adjektibo, etab.) ere erabili daitezke. Halakoei ezaugarri deitzen zaie, eta beraz hitz baten testuinguru sintaktikoa corpusetatik erautsitako ezaugarriez (hau da, hitzaren agerpenetan bere inguruan azaltzen diren kategoria zein argumentu egiturak) errepresentatzen da. Horrelako ezaugarriak adiera desanbiguaziorako erabiltzen dira zuzenean (ikusi IV.A.4 atala), baina erlazio-izaera formalizatzeko zeharka erabili behar da: testuinguru beretsuetan azaltzen diren hitzak erlazionatuta daude. Hala egiten du Grefenstette-ek (1992; 1996) hitzen arteko erlazio-izaeraren neurria halako pista sintaktikoen gainean definitzerakoan. Ebaluazio interesgarria egiten du, Richardson-en antzekoa, thesaurus-ak erabiliz erlazio-izaeraren estandar bezala.

Corpus/ sintagmatiko globala/ hitzak/ gutxi/ izenak/ emaitza onak/ datu urrien arazoa

Lan batzuetan zuzenean jotzen da erlazio sintaktiko berezi baten azterketara. Hala da aditzaren hautapen-murrizpenaren inguruan egiten diren azterketa gehienetan, adibidez Grishman eta Sterling-en lanean (1994) edo Lee-ren tesian (1997). Hauek corpus zabaletatik aditz-objektu pareak atera eta aditz bakoitzak hobesten duen izenen klasea topatzen saiatzen dira, aditz eta izenen arteko erlazio-izaera definituaz.

Corpus/ sintagmatiko globala/ hitz/ gutxi/ izenak/ emaitza onak/ datu urrien arazoa

III.A.4. Ontologia eta corpusen arteko konbinazioak

Hainbat lanek aurreko hurbilpenak hedatu beharra dagoela diote. Arrazoi anitz aipatzen dute. Nagusiena, goiko teknika guztiek hiztegia egitura semantiko gabeko zerrenda bezala tratatzen dutela da. Hitzak eta kontzeptuak klaseetan eratu ohi dira, eta hitz baten ezaugarri semantiko asko bere klasearenak dira. Horretara, zertarako gorde informazioa hitzez-hitz, zati handi bat klasearen ezaugarria baldin bada? Bestalde, hurbilpen estatistikoaren aldekoen buruhauste nagusiak (**datu urrien arazoa** eta **eskuzko desanbiguazioaren beharra**) gutxitu litezke hitzak sailkatuta edukiz gero. Adibidez, jan aditzaren objektu tipikoak adierazteko hobe da *gauza-jangarri* klasea erabiltzea, banan-banan *otarteko*, *urdaiazpiko*, *legatz*, *sagar*, etab. zerrendatzea baino. Gainera, nahiz eta kiwi ez azaldu inoiz corpusean *jan*-en objektu bezala, *gauza-jangarri* bezala sailkatuta badago gai izango gara *kiwi* eta *jan*-en arteko erlazioa asmatzeko.

Lan batzuek klase horiek corpusetik bertatik erauzten dituzte (adibidez lehenago aipatutako Schütze-ren lanak) baina horrek askotan errore-zama bat sartzen du. Horren aurrean askok thesaurus edo ontologietara jotzea proposatzen dute, klaseen definizio intuitibo eta zuzenen bila. Yarowsky-k (1992), adibidez, kategoria bezala Roget thesaurusak emandakoak erabiltzen ditu, adiera-desanbiguazio lan batean. Roget thesaurusean (ikus II.A.2 atala) klase bakoitzeko hitz zerrenda bat dator. Klase bakoitza agertzen den testuinguru tipikoak zeintzuk diren jakiteko klaseko hitzak agertzen diren 100 hitzetako leihoak jasotzen ditu Grolier entziklopediatik. Testuinguru horien arabera, kategoria bakoitzerako hitz adierazgarrienak[32] biltzen ditu, nabarmentasun (*saliency*) izeneko neurri estatistikoaren arabera (ikus 10. ekuazioa).

$$\text{saliency}(w) = \log \frac{\Pr(w \mid c)}{\Pr(w)} \qquad (10)$$

Lan honetan ez da esplizituki azaltzen hitzen arteko erlazio-izaera, hitzak Roget-eko klaseekin etiketatzeko metodoa baizik. Hala ere, corpusen inguruko beste lanetan bezala, neurri hauetatik posible liteke hitz edo adieren arteko erlazio-izaera kalkulatzea. Basili-k eta (Basili et al. 1995; 1997; Cucchiarelli & Velardi 1997) ere antzeko neurria erabiltzen dute ontologietarako informazioa erauzi nahian.

Ontologia+corpus/ sintagmatiko globala/ kontzeptuak/ zabal/ izenak/ emaitza oso onak/ datu urrien arazorik ez

Resnik-ek (1993a; 1993b; 1995; 1997), aldiz, beste era batera konbinatzen du corpuseko eta ontologiako informazioa. Bi adieren arteko erlazio-izaera neurtzeko ontologian amankomunean duten arbaso hurbilena bilatzen du, baina distantzia neurtu ordez, klase horren informazio-edukia (*information content*) kalkulatzen du (ikusi 11 formula, non v eta w izenak diren, eta c izen horiek biltzen dituen klase txikiena).

[32] Yarowsky-ren hitzetan "*words that are likely to co-occur with the members of the category*".

$$\text{antzekotasuna}(v, w) = -\log \Pr(c) \tag{11}$$

Klasearen probabilitatea klase horren kide diren hitzek corpusean duten maiztasunetatik estimatu daiteke:

$$\Pr(c) \cong \frac{\sum_{w \in c} f_w}{N} \tag{12}$$

Neurri hauek aditz eta izenen adieren arteko erlazioaren indarra neurtzeko soilik erabili izan ditu, aditzen hautapen-murrizpenak eskuratzeko bidean. Ebaluazio zeharkakoa egin zuen, izenen adiera-desanbiguazioan eta aditzen hautapen-murrizpenen bilaketan. Li eta Abe-k (1995; 1996) ere hurbilpen hau erabiliko dute hautapen-murrizpenen indukzioan eta izenen multzokatze automatikoan.

Ontologia+corpus/paradigmatikoa/kontzeptuak/gutxi/izenak/emaitza onak/datu urrien arazorik ez

Schütze-ren aurreko lanean (1992a; 1992b) aurkeztu zen hitzen arteko erlazio-izaera WordNet-eko informazio hierarkikoarekin konbinatzen saiatzen dira Hearst eta Schütze (1993). Helburu bezala hierarkiaren bidez erlaziorik ez duten kontzeptuak erlazionatzea jartzen dute, adibidez pilota eta frontoia, baina azkenean egiten dutena zera da, WordNet-eko izenen sysnset guztiak 726 kategoriatan banatu eta horien arteko erlazioak landu. Emaitzen ebaluazio sistematikorik ez dago, eta autoreek beraiek aitortzen dute erlazio gutxi lotu dituztela. Lortutako sare kontzeptual berrirako ez du erlazio-izaera neurri berririk ematen.

Ontologia+corpus/sintagmatiko globala eta lokala/kontzeptuak/gutxi/izenak/emaitza onak/ datu urrien arazorik ez

Ontologiak baino hiztegiak erabiltzen dituzte Karov eta Edelmann-ek (1996; 1998) hitz baten adiera bati lotuta dauden testuinguruak (esaldiak kasu honetan) lortzeko. Erlazio-izaeran zirkularitate bat dagoela iruditzen zaie: hitzak erlazionatuta daude esaldi beretsuetan azaltzen badira, eta esaldiak erlazionatuta egongo dira erlazionatutako hitzak badituzte. Zirkularitate hori puskatzeko algoritmo iteratibo bat erabiltzen dute, euren esanetan konbergentziara heltzen dena. Beraien hurbilpenaren abantaila bat datu gutxiagorekin entrenatzeko gai direla izango litzateke.

Hiztegia+corpus/sintagmatiko globala/kontzeptuak/gutxi/izenak/emaitza onak/datu urrien arazorik ez

III.B. Dentsitate Kontzeptuala

Ontologian oinarritutako erlazio-izaera formalizatzeko gure proposamena aurkeztuko dugu atal honetan. Formalizazio horrek honako baldintza hauek edukitzea nahi dugu:

1. Ontologiatan oinarritutakoa.
2. Adieren arteko neurria: ontologiako kontzeptuei erreferentzia egingo diena
3. Erlazio paradigmatiko eta sintagmatikoetako informazioa erabiliko duena
4. Kategoria irekietako[33] hitzekin lan egingo duena
5. Eraginkorra izatea, testu zabalekin lan egin ahal izateko bezalakoa.

Lehenbiziko bi baldintzak lotuta daude, ontologia erabiltzen denean kontzeptuen arteko erlazioak berez landuta daude eta. Ontologian erlazio paradigmatiko eta sintagmatikoek egon beharko dute, erlazio-izaera zenbaiterainokoa den erabakitzean ahal den informazio gehien izan dezagun. Ontologia erabiltzearen beste abantaila informaziorik ikasteko beharrik ez dagoela da, hau da, ez da beharrezkoa aurrez eskuz ezer desanbiguatzea. Azkenik izen, adjektibo eta aditzekin lan egiteko balio behar du, eta testu errealekin lan egitea nahi dugu, ez ordea dozena eskas hitz konkreturekin.

Baldintza horiek betetzen saiatuko diren bi formula aurkeztuko ditugu. Lehenbizi 2 kontzepturen arteko neurria ematen duena, eta ondoren edozein kontzeptu multzorako neurria.

III.B.1. Bi kontzepturen artekoa: Distantzia

Rada (Rada et al., 1989) eta bereziki Sussna-ren (1993) lana hartu dugu abiapuntu bezala. Lan horien arabera erlazio-izaera ontologiako kontzeptuen arteko Distantzia Kontzeptualaren[34] bidez kalkula daiteke[35]. Sussna-k egindako ikerketaren arabera bi faktorek daukate zerikusia Distantzia Kontzeptuala kalkulatzean: bi kontzeptuen arteko erlazio-bidearen luzera (bide luzeagoa den heinean distantzia handiagoa) eta bide horretan dauden kontzeptuen sakonera (sakonean dauden kontzeptuen artean distantzia txikia). Horren arabera ondoko formula proposatu genuen (Agirre et al., 1994b):

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[33] Horrela izendatu ohi dira izen, aditz eta adjektiboak.

[34] Kapitulu honen hasieran aipatu dugu distantzia semantikoa, erlazio-izaera bera definitzen ari ginenean. Distantzia semantikoa formalizatu gabe egonik, guk ontologia batera lotu dugu, eta horregatik deitzen diogu distantzia kontzeptuala.

[35] Erlazio-izaera eta Distantzia Kontzeptuala alderantzizkoak dira: hertsiki erlazionatuta dauden kontzeptuen artean distantzia kotzeptuala 0ren hurrena da, eta erlaziorik ez duten bi kontzepturen arteko distantzia kontzeptuala ∞-rantz hurbiltzen da.

$$\mathrm{Dist}(a,b) = \min_{p \in \mathrm{bide}(a,b)} \sum_{c_i \in p} \frac{1}{\mathrm{sakonera}(c_i)}$$
$$\text{non } a = c_0 \text{ eta } b = c_n \tag{13}$$

Bi kontzepturen (13. ekuazioko *a* eta *b*) arteko Distantzia Kontzeptuala bide (*p*) motzenak emango digu, luzera modu berezi batean kalkulatuz gero: bideko kontzeptu bakoitzarengatik hierarkian duen sakoneraren alderantzizkoa gehituko dugu. Honek islatzen duena zera da, zenbat eta gertuago eta sakonago egon kontzeptuak ontologian, orduan eta Distantzia Kontzeptual txikiagoa egongo da bien artean (Agirre et al. 1994b).

III.B.2. N kontzepturen artekoa: Dentsitatea

Distantzia hau baliagarria da bere horretan aplikazio askotan, baina bi kontzepturen distantzia N kontzeptutara orokortu nahi badugu leherketa konbinatorio bat sortzen da. Binakako distantzia erabiliz N kontzepturen arteko distantzia neurtzeko modua pare posible guztien distantziak batzea da (Sussna, 1993). Zortzi kontzepturen arteko distantzia kalkulatzeko, adibidez, zortziren binakako konbinazio guztiak, 28, eduki behar dira kontutan[36]. Esaldi bateko hitzen arteko distantzia neurtu nahiko bagenu gauzak okertu egiten dira, hitzen anbiguetatea dela medio. Demagun esaldiak 8 hitz dauzkala, eta bakoitzak 3 adiera, adiera guztien arteko binakako distantziak kalkulatu behar izanez gero hitzen arteko binakako pare guztiak (28 berriz ere) adiera konbinazio guztientzat (3^2) probatu beharko dira: guztira 252. Orokorrean N hitz badaude, batez beste M adiera dituztenak $\binom{N}{2} \times M^2 = \frac{N \times (N-1)}{2} \times M^2$ aldiz neurtu beharko dugu bi kontzepturen arteko distantzia.

Bestalde, kontzeptu multzoen arteko konparazioak zaildu egiten dira. Demagun A eta B multzo bakoitzean bi kontzeptu dugula. Horrela posible da esatea A-ko bi kontzeptuak B-ko biak baino elkarrengandik gertuago daudela. Pare ezberdinen arteko distantziak konpara daitezke. Baina, A multzoari beste kontzeptu bat gehituz gero distantzia handitu egingo da, eta ezinezkoa da A berri honen distantzia B-renarekin alderatzea, kontzeptu kopuru ezberdinaren distantzia neurtzen ari garelako.

Hori dela eta, lehen aipatutakoez gain, beste baldintza pare bat gehituko diogu gure neurriari:

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36 $\binom{8}{2} = \frac{8 \times 7}{2} = 28$

6. N kontzepturen arteko neurria izatea
7. Kontzeptu kopuru ezberdineko multzoen gertutasunak konparagarriak izatea.

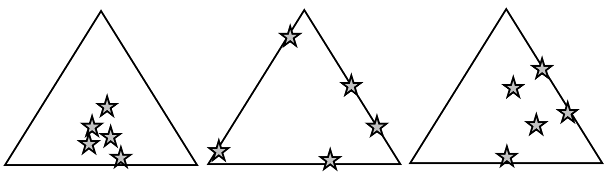
Lehenbiziko baldintzara bueltatuz gero, neurria errealitatean aplikatzeko ontologia bat aukeratu beharra dago. Tamalez, gaur egun, ontologia zabal eta libre eskuragarri gutxi daude, hiztegi aldetik zabala dena bakarra: WordNet (ikusi honi buruzko eztabaida II.C atalean). WordNet-en ezaugarri batek eragina edukiko du ezarritako beste baldintza batetan, erlazio paradigmatikoa baita gehienbat landua dagoena. WordNet aukeratzeak eragin digu hirugarren baldintza, gogoz kontra, murriztu behar izatera:

1. WordNet ontologian oinarritutakoa
3. Erlazio paradigmatikoetako informazioa erabiltzen duena

Autore batzuen ustez, erlazio paradigmatikora mugatzea ez da hain murrizpen gogorra: "*we hypohesize that … is strong enough for the length of is-a paths to be used as a measure of semantic relatedness*" (Rada et al., 1989). Erlazio hierarkikoak soilik erabiltzeak, gainera, efizientzia aldetik sekulako hobekuntza ekarriko digu, gero ikusiko dugun bezala.

N kontzepturen arteko neurria garatzea ez da hain gauza naturala. Orain arte nahiko garbi zegoen bi kontzepturen arteko bidearen luzera dela gure formulazioaren muina, eta sakonera ere kontuan hartu beharra dagoela. N kontzepturen arteko neurriak ordea beste jite bat hartu behar du, eta distantzia baino dentsitatea izango da kontuan hartu beharrekoa: bideen luzera baino azpizuhaitzetan dauzkagun kontzeptuen kopuruak. Harira joan aurretik, aurrerantzean nahasteak saihesteko terminologia kontua: kontzeptu-multzo batean erlazio-izaera neurtu nahi dugunean, multzoko kontzeptuei **arrasto** deituko diegu, azpizuhaitzeko beste kontzeptuekin ez nahasteko.

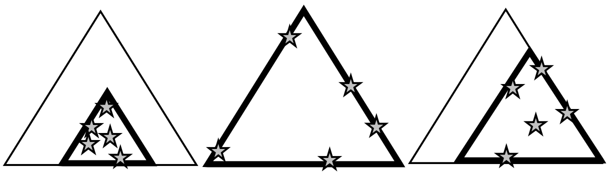
Neurri honen muina galdera honetatik dator: zenbat arrasto behar dira ontologiako azpizuhaitz batean, azpizuhaitz hori arrastoz asea edo betea dagoela esateko? Edo beste modu batera esanda, bi azpizuhaitz konparatzean nola neurtu dezakegu zein den beteago dagoena?



1. irudia: azpizuhaitz bera hiru arrasto multzo ezberdinekin.

1. irudian ontologiaren zati bera hiru arrasto multzo ezberdinekin azaltzen da. Hiru kasuetan arrastoen arteko gertutasuna berdina dela esango genuke? Ez. Badirudi erlazio-izaera handia izan beharko litzatekeela ezkerrekoarentzat, txikia erdikoarentzat eta tartekoa eskuinekoarentzat (edo dentsitateari buruz bagabiltza, dentsitate handiena ezkerrekoak eta txikiena erdikoak). Binakako Distantzia Kontzeptuala erabiliko bagenu emaitza bera jasoko genuke, hau da, ezkerreko arrastoen artean bide motzak daude, eta erdikoaren artean bide luzeak.

Bideak alde batera utziz, hiruen arteko ezberdintasun bat zera da, zein den 5 arrastoak estaltzen dituen azpizuhaitz minimoa, 2. irudian azaltzen den bezala.



2. irudia: arrasto multzoak estaltzen dituzten azpizuhaitz minimoak (marra lodiagoz).

Azpizuhaitz horiek kontuan hartuz nahiko garbi azaltzen da arrastoen arteko erlazio-izaerak azpizuhaitz minimoaren arteko tamainarekin[37] erlazio zuzena duela: Dentsitate handienekoak tamaina txikiena du (ezkerrekoak), eta dentsitate gutxienekoak tamaina handiena (eskuinekoak). Hemendik soma daiteke Dentsitate deituko dugun hori arrasto kopuruaren eta azpizuhaitz minimo horren tamainaren arteko erlazioa dela. Lehenbiziko hurbilpen batean, adibidez, a arrasto estaltzen dituen Z azpizuhaitzaren Dentsitatearen neurrirako 14. ekuazioa dugu, hau da, arrasto kopurua (a) zati zuhaitzaren tamaina (zuhaitzaren azalera ere deituko duguna).

$$\text{dentsitate}(Z, a) = \frac{a}{\text{azalera}(Z)} \tag{14}$$

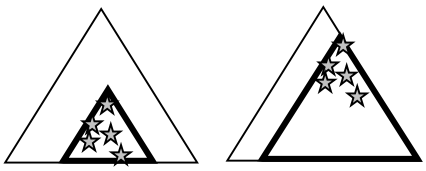
Eta zein izango da arrasto multzo baten Dentsitatea? Arrasto multzoa (demagun A dela) estaltzen duen azpizuhaitz minimoaren Dentsitatea, edo beste era batera esanda A multzoko arrastoak estaltzen dituzten azpizuhaitz guztietatik, Dentsitate maximoa lortzen duenaren Dentsitatea, 15. ekuazioan[38] azaltzen den bezala.

[37] Honako hirurak gauza bera adierazten dute: azpizuhaitz baten adabegi kopurua, tamaina eta azalera.

[38] Z azpizuhaitzak A estaltzen duela adierazteko $A \cap Z = A$ erabiltzen da, eta A multzoan dagoen arrasto kopurua adierazteko bere kardinala $|A|$.

$$\text{dentsitate}(A) = \max_{Z,\ \text{non}\ Z \cap A = A} \text{dentsitate}(Z, |A|) \qquad (15)$$

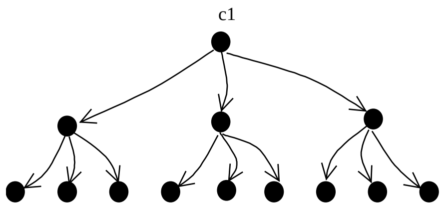
14. ekuaziora itzuliz, Distantzia Kontzeptualaren ezaugarri nagusiak biltzen ditu: gertutasuna eta sakonera. Zenbat eta gertuago egon, orduan eta txikiagoa izango baita arrastoak estaltzen dituen azpizuhaitz minimoaren azalera. Sakonerarekin beste hainbeste: arrastoak sakonago egonda azpizuhaitz minimoa txikiagoa izango da eta. Esandakoaren adibideak aurki daitezke 2. eta 3. irudietan: bietan Dentsitate handieneko arrasto multzoak ezkerrekoak dira.



3. irudia: arrasto multzoak estaltzen dituzten azpizuhaitz minimoak (marra lodiagoz).

14. ekuazioko neurri honek, ordea, arazo asko ditu. Hauek aztertu aurretik zuhaitzen topologiari buruzko neurri batzuk eta beraien arteko erlazioa definituko ditugu: azpizuhaitzaren altuera (h_Z), zuhaitzeko kontzeptuek batez beste duten ume kopurua (μ_Z, adarkatze faktorea ere deitua – *branching factor*), eta azpizuhaitzaren azalera, azpizuhaitzak dituen kontzeptu kopuruak ematen duena. Hiru neurri hauen arteko erlazioa 16. ekuazioak jasotzen du. Neurri hauen adibidea 4. irudian azaltzen den azpizuhaitz erregularrak ematen digu.

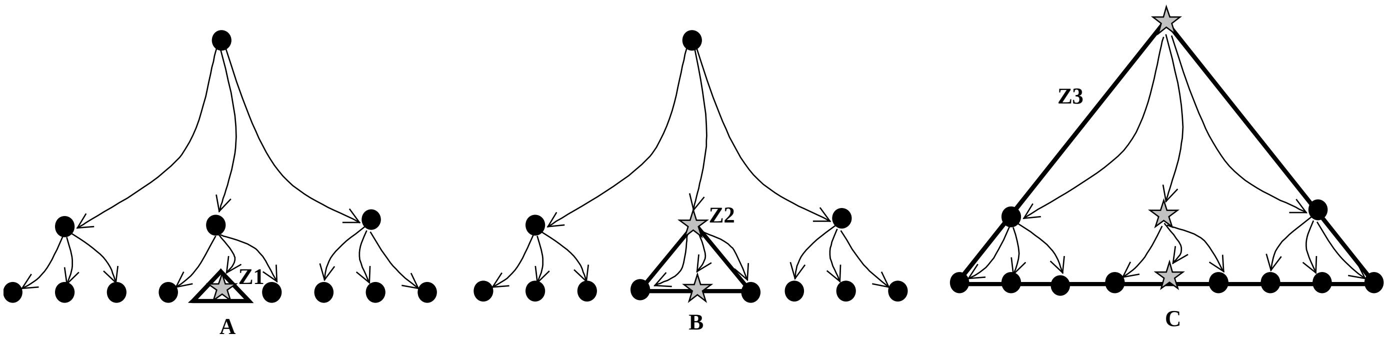
$$\text{azalera}(Z) = \text{kontzeptu\_kop}(Z) = \sum_{i=0}^{h_Z - 1} (\mu_Z)^i \qquad (16)$$



4. irudia: c1-en erroa duen azpizuhaitzaren altuera (3 maila), batezbesteko ume kopurua (3), eta azalera edo kontzeptu kopurua ($13=3^0+3^1+3^2$).

14. ekuazioak dituen arazoak 7. ezaugarritik datoz, hau da, kontzeptu kopuru ezberdineko multzoen arteko gertutasunak konparatu nahi izateagatik. Aztertu ahal izateko, demagun hiru kontzeptu

multzoren Dentsitatea neurtu nahi dugula (A, B eta C multzoak): batek arrasto bakarra, besteak bi eta azkenak hiru dituena, 5. irudian azaltzen den bezala. Arrasto multzo bakoitza estaltzen duen azpizuhaitza hiruki bezala marraztua dago.



5. irudia: hiru arrasto multzo azpizuhaitz berean. Kontzeptuak ● bidez adierazita daude, eta arrastoak ☆.

Intuitiboki zer esango genuke? B multzoko kontzeptuak C multzokoak baino estuago daudela erlazionatuta? Edo bi multzoek erlazio-izaera neurri berdina beharko luketela? Guk formalizatu nahi dugun erlazio-izaerarentzat garbi dago B eta C multzoko kontzeptuen artean gertutasun berdina dagoela. 14. ekuazioak, aldiz, bestela esaten digu:

dentsitate(A) = dentsitate(Z1,1) = 1/1 = 1

dentsitate(B) = dentsitate(Z2,2) = 2/4 = 0,5

dentsitate(C) = dentsitate(Z3,3) = 3/13 = 0,23

Gure ustez hiru arrasto multzo horien Dentsitatea 1 izan beharko litzateke, eta horretarako arrastoak kontatu baino, bestelako erreferentzia bat behar dugu: azalera eta arrastoen kopuruen arteko erlazioa ez da nahiko, altuera ere hartu beharko dugu kontuan. Adibidez, 5. irudian Z1 azpizuhaitzaren altuera 1 da eta arrasto bat du, Z2-ren altuera 2 da eta 2 arrasto ditu, eta Z3-ren altuera 3 izanda 3 arrasto dauzka, hiru kasuetan batezbesteko ume kopuruak berdinak direlarik.

Beste modu batera ikusita, nolako pisua eman beharko litzaioke arrasto bakoitzari 5. irudiko arrasto multzoen Dentsitatea 1 izan zedin? Galdera honi erantzun aurretik, idatz dezagun 14. ekuazioa beste modu batera, azaleraren ordez 16. ekuazioko formula jarriko dugu (ikus 17. ekuazioa), zatikizuna arrasto kopuruaren funtzio ezezagun bezala utziz –f(a).

$$\text{dentsitate}(Z,a) = \frac{\text{f}(a)}{\text{azalera}(Z)} = \frac{\text{f}(a)}{\sum_{i=0}^{h_Z - 1} (\mu_Z)^i} \tag{17}$$

Demagun 3 zuhaitz horientzat Dentsitate bera lortu nahi dugula, eta gainera horien Dentsitatea 1 izatea nahi dugula. Bilatzen dugun erlazioa altuera eta arrasto kopuruaren artekoa izan behar denez, eta altuera zatitzailearen batukarian azaltzen denez, 17. ekuazioaren zatikizunean zatitzailearen formula bera jarriko dugu, baina altuera dagoen lekuan arrasto kopurua jarriaz (18. ekuazioa)

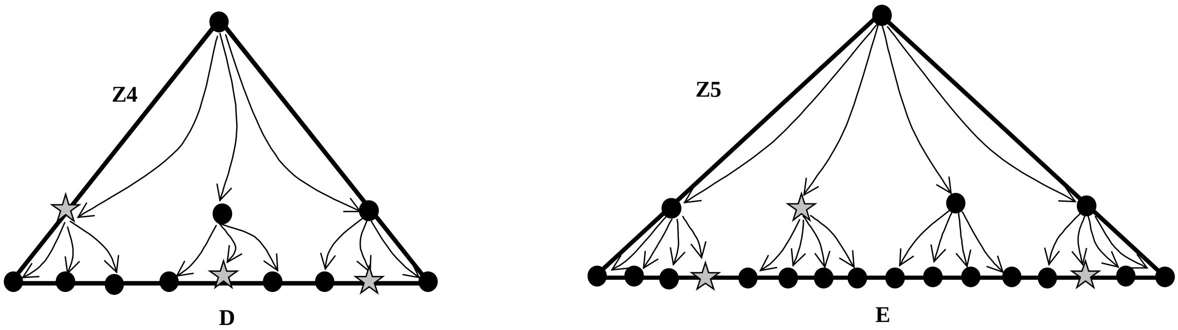
$$\text{dentsitate}(Z,a) = \frac{\sum_{i=0}^{a-1} (\mu_Z)^i}{\sum_{i=0}^{h_Z - 1} (\mu_Z)^i} = \frac{\sum_{i=0}^{a-1} (\mu_Z)^i}{\text{azalera}(Z)} \tag{18}$$

18. ekuazioko zatitzaileak azpizuhaitzaren azalera adierazten du, eta zatikizunak *a* arrastoko eta batezbesteko ume kopuru bereko zuhaitz erregularrak Dentsitatea 1 izateko eduki beharko lukeen azalera. Beste era batera esanda, zatikizunak 1 Dentsitatea eta μ_Z batezbesteko ume kopurua dituen zuhaitz erregularra errepresentatzen du, altuera eta arrasto kopurua berdinak dituena. Horrela islatzen da arrasto eta azpizuhaitzaren azaleraren arteko erlazioa.

14. ekuazioak bazeukan beste arazo bat arrasto multzo ezberdinen artean konparatzean, topologiarekin zerikusia duena. Ezaguna da ontologiaren zatiek topologia ezberdina eduki ohi dutela; alderdi batzuk kontzeptuz aberatsak direla, eta beste batzuk pobreagoak. Alderdi aberatsetan batezbesteko ume kopurua handia izango da, eta alderdi pobreetan txikia. Demagun bi kontzeptu multzo ditugula, biak hiru arrastokoak (6. irudiko D eta E), baina ontologiaren eremu ezberdinetan daudenak. Halakoetan, distantzia berera daude D-ko kontzeptuak eta E-ko kontzeptuak, baina 14. ekuazioaren arabera Dentsitate ezberdina izango dute:

dentsitate(D) = dentsitate(Z4,3) = 3/13 = 0,23

dentsitate(E) = dentsitate(Z5,3) = 3/21 = 0,14



6. irudia: Dentsitatea 1 duten neurri ezberdineko bi azpizuhaitz

18. ekuazioa erabiliaz, aldiz, orain arte erakutsi ditugun kontzeptu multzo guztietan Dentsitatea 1 da, guk nahi genuen bezala[39]:

dentsitate(A)=dentsitate(Z1,1) = 1/1 = 1

dentsitate(B)=dentsitate(Z2,2) = (1+3)/4 = 1

dentsitate(C)=dentsitate(Z3,3) = (1+3+9)/13 = 1

dentsitate(D)=dentsitate(Z4,3) = (1+3+9)/13 = 1

dentsitate(E)=dentsitate(Z5,3) = (1+4+16)/21 = 1

Kontzeptu multzo baten dentsitate kontzeptuala, beraz, 15. eta 18. ekuazioen bidez definituko dugu tesi lan honetan.

III.C. Inplementazioa

Dentsitate Kontzeptuala WordNet-eko hiperonimia erlazioa erabiliaz inplementatu dugu. Distantzia Kontzeptuala bai WordNet eta bai LPPL Hiztegi-Ezagutza Baserako inplementatu dugu. Tesi-lan honetan Dentsitateari buruz arituko garenez, ez dugu azalduko Distantziaren inplementaziorik. Inplementazio bera azaldu aurretik, parametroei buruz arituko gara.

III.C.1. Dentsitate Kontzeptualaren aldaerak

Dentsitate Kontzeptuala inplementatzean parametro eta aldaera batzuk ikertzea interesgarria izan daitekeela ikusi dugu. Horien artean egokiena zein izango den aldez aurretik erabakitzea zaila denez, enpirikoki aplikazio batean lortutako emaitzen arabera egitea erabaki genuen. Aplikazioa hitzen adiera-desanbiguazioa da. Atal honetan parametro eta aldaerak aurkeztuko ditugu, eta esperimentuen emaitzen berri IV.C.2 atalean emango dugu.

[39] Gogoratu azpizuhaitz guztietarako μ_Z 3 dela, Z5-entzat ezik, honentzat μ_Z 4 baita.

III.C.1.a) *Parametroa:* α

Dentsitate Kontzeptualaren formulak arazo txiki bat dauka: azpizuhaitz baten azpian dagoen arrasto kopurua oso handia denean, 18. formulako zatikizuna gehiegi handitu daiteke. Izan ere, Dentsitatea 1 izan dadin altuera eta arrasto kopurua berdina izatea eskatzen dugu, baina erabaki hau erabat arbitrarioa da. Dentsitatea 1 izateko altuera eta arrasto kopuruaren arteko erlazioa aldatzeko, α parametroa gehitu genion formulari, enpirikoki aztertu eta balioa bilatu dioguna. Parametrodun formula 19. ekuazioan azaltzen zaigu.

$$\mathrm{dentsitate}(Z,a) = \frac{\sum_{i=0}^{a-1} (\mu_Z)^{i^{\alpha}}}{\mathrm{azalera}(Z)} \qquad (19)$$

III.C.1.b) *Nola kalkulatu* μ*:* μ_Z *eta* μ_{WN}

Dentsitate Kontzeptuala kalkulatzerakoan zuhaitzaren topologia (μ_Z batezbesteko ume kopuruaren bidez islatzen duguna) kontuan hartzea garrantzizkoa da. Egikaritzapen-garaian konputatzea garestia izan daiteke, eta ontologia hierarkikoa izanda komenigarriagoa dirudi aldez aurretik azpizuhaitz posible bakoitzarentzat konputatua edukitzea. Horrekin batera azpizuhaitz bakoitzaren azalera ere gorde daiteke. Dentsitatea kalkulatzean nahikoa litzateke azpizuhaitzari dagozkion μ_Z eta azalera taula batetik atzitzea.

Aurrerago ikusi dugu azpizuhaitz baten batezbesteko ume kopurua, azpizuhaitzaren altuera (h_Z) eta azalera (*azalera(Z)*, adabegi kopurua) erlazionatzen dituen ekuazioa (ikus 16. ekuazioa). 7. irudian azaltzen da altuera (H) eta azalera (A) emanda batezbesteko ume kopurua (μ) kalkulatzeko erabili dugun programazio linealeko pseudokodezko algoritmoa. Parametro bezala, emaitzari eskatzen zaion doitasuna (d) eman beharra dago.

```
Sarrera:        H altuera, A azalera
Irteera:        μ batezbesteko ume kopurua
Parametroa:     d doitasuna
Aurrebaldintza: A>H

   baldin 1 <= A < H
      orduan  μ := 1 - 1/a
      bestela μ := a^(1/n)
   ambaldin
   bigizta
      s := μ^n;
      e := (μ*(s-A) + A - 1)/(H*s - A);
      μ := μ - e;
   harik eta |e/μ| < d ambigizta
```

7. irudia: μ_Z konputatzeko algoritmoa

Bestalde, μ_Z lokala erabili ordez, WordNet ontologia osoarentzat kalkulatutako batezbesteko ume kopurua erabiliko bagenu (μ_{WN}), Dentsitateak okerrago egingo lukeela espero daiteke. Hau horrela den edo ez neurtzeko aipatutako esperimentuak egin ditugu, IV.C.2 atalean azalduko ditugunak.

III.C.1.c) WordNet-eko beste erlazioak: meronimia

Dentsitate Kontzeptualak hiperonimia besterik ez du erabiltzen. Hala ere WordNet-eko izenen artean badaude beste erlazio hierarkikoak, meronimikoak (ikus II.C.3 atala). Printzipioz, are eta erlazio mota gehiago hartu kontutan, are eta emaitza hobeagoak espero daitezke. Meronimia erlazioa erabiliaz emaitza hobeagoak lortu diren edo ez enpirikoki aztertu dugu (ikus III.C.1.c) atala). Dentsitate Kontzeptualaren formulari dagokionez, ez dugu ezer aldatu meronimia kontuan hartzeko. Azpizuhaitzen azalera kalkulatzean, edo adiera bat bestearen azpian dagoen erabakitzean, ez dugu bereiziko hiperonimia edo meronimia erlazio artean.

III.C.2. WordNet-en gaineko inplementazioa

WordNet-erako egindako inplementazioan erlazio hierarkikoak besterik erabiltzen ez ditugunez, horretaz baliatzen den algoritmo eraginkorra diseinatu dugu.

Dentsitatea neurtzerakoan, adiera multzo bat (AM) ematen digute, arrasto ere deitu ditugunak. Adiera horientzat WordNet-en azpimultzoa den hierarkia eraikitzen dugu, arrastoen hiperonimo kateak jarraituaz. Hierarkia horretan egongo dira kontuan hartu behar ditugun azpizuhaitz guztiak. Izan ere, azpian arrasto bat ez badu azpizuhaitz batek, horren Dentsitatea 0 izango da. 8. irudian azaltzen da hierarkia hori eraikitzen duen algoritmoa. Adiera (arrasto) multzo bat emanda, kontuan hartu beharreko azpizuhaitz guztiak dauzkan hierarkia (`H`) bueltatzen digu. `H` aldagaia egitura bat da: `hipo` eremuan hierarkiago adabegi bakoitzaren hiponimoa gordetzen da, `arrasto_kopurua` eremuan adabegi bakoitzaren azpian dagoen arrasto kopurua, eta `azpizuhaitzak` eremuan adabegi guztien zerrenda. 8. irudiko algoritmoa sinplifikazio bat da, adiera bakoitzarentzat hiperonimo bakarra suposatzen baitu (zuhaitz egitura izango balitz bezala). Hori ez da beti horrela WordNet-en. Hori konpontzeko `eman_hiperonimo_katea` funtzioak kate bat baino gehiago itzuliko luke, zerrenda bat eduki beharko luke.

```
FUNTZIOA: Eraiki_hierarkia(AM)
   Sarrera:  AM arrasto multzoa
   Irteera:  H hierarkia

      bigizta A barne AM bakoitzeko
         hiper_katea := eman_hiperonimo_katea(A) ;
         hipo := A ;
         bigizta h barne hiper_katea bakoitzeko
            H.hipo[h] = hipo ;
            H.arrasto_kopurua[h] ++ ;
            hipo := h ;
            sartu(h,H.azpizuhaitzak) ;
         ambigizta
      ambigizta
      bueltatu(H)
```

8. irudia: Dentsitate Kontzeptuala neurtu behar den arrastoen hiperonimoekin hierarkia eraikitzea

19. ekuazioaren inplementazioa 9. irudian dago. Arrasto kopuru jakin bat duen azpizuhaitz baten Dentsitatea kalkulatzen du, α parametroaren arabera. Funtzioaren argumentuak azpizuhaitza bera eta horren azpian dagoen arrasto kopurua dira. Dentsitatea kalkulatu ahal izateko azpizuhaitz horren azalera (`Z.azalera`) eta batezbesteko hiponimo kopurua (`Z.μ`) jakin behar ditu (aldez aurretik kalkulatu ditugunak, ikus III.C.1.b) atala).

```
FUNTZIOA:   DK(Z,A)
   Sarrera:    Z  azpizuhaitza
               A  arrasto kopurua
   Irteera:    DK dentsitate kontzeptuala
   Parametroa: α
   Datuak:     Z.azalera
               Z.μ

      d1 := 0
      i := 0
      bitartean i < A
         d1 := d1 + Z.μ ^ (i^α)
      ambitartean
      DK := d1/Z.azalera
      bueltatu(DK)
```

9. irudia:Dentsitate Kontzeptuala kalkulatzeko algoritmoa

Azkenik, edozein arrasto multzo baten Dentsitate Kontzeptuala jakiteko, 15. ekuazioa jarraituz, arrasto multzo hori estaltzen duten azpizuhaitzen artean Dentsitate Kontzeptual altuena zeinek duen kalkulatu beharko dugu. 10. irudiko algoritmoak hori bera egiten du. Arrasto guztiak estaltzen dituzten azpizuhaitzetatik (`H.azpizuhaitzak`) Dentsitate altuenekoaren Dentsitatea itzultzen du.

```
FUNTZIOA:   DK(AM)
   Sarrera:    AM arrasto multzoa
   Irteera:    DK dentsitate kontzeptuala

      DK := 0 ;
      H := Eraiki_hierarkia(AM) ;
      bigizta Z barne H.azpizuhaitzak bakoitzerako
         d := DK(Z,H.arrasto_kopurua[Z]) ;
         baldin d > DK orduan DK := d ;
      ambigizta
      bueltatu(DK)
```

10. irudia: adiera multzo baten Dentsitatea

III.D. Ebaluazioa eta besteekiko alderaketa

Dentsitate Kontzeptuala eta Distantzia Kontzeptuala tesi honetan definituta bezala (15. eta 18. ekuazioak) ez ditugu zuzenean ebaluatu, hau da, ez ditugu erlazionatutako hitz multzoen zerrendekin probatu jakiteko ea ekuazioetako erlazio-izaeraren neurria eta giza-sena bat datozen, gorago aipatutako arrazoiengatik (ikusi III.A atalean ebaluazioari buruzko gogoeta). Ebaluazioa Dentsitatea erabili den aplikazio bakoitzaren arabera egingo da, beste sistemek lortutako emaitzekin alderatuaz (ikusi IV.D atala bereziki, baina baita ere VI eta I.A.1)

Atal honetan emaitzen ebaluazioa baino ezaugarrien alderaketa egingo dugu beste sistemekiko, helburua honako baieztapen hau arrazoitzea izanda:

> *Nahiz eta zeregin batzuetan emaitza onenak lortu ez , bai oinarri teorikoaren aldetik baita zeregin ezberdinetarako prestatuta egoteagatik ere, ontologian oinarritutako erlazio-izaeraren formalizazioak hobeak dira, eta ontologietan oinarritutakoen artean Dentsitatea orokorragoa, eraginkorragoa eta emaitza onenak dituena da.*

Baieztapen honetako bi oinarriak, ontologian oinarritutako tekniken nagusitasuna eta ontologian oinarritutakoen artean Dentsitatearen abantailak, aztertuko ditugu orain. Hurrengo kapituluan (IV) aplikazio konkretu baten lortutako emaitzetan oinarrituta alderatuko dugu Dentsitate Kontzeptuala beste lanekin.

III.D.1. Ontologiatan oinarritutako tekniken nagusitasunaren inguruan

Lehenbiziko aztergaia ontologian oinarritutakoen nagusitasuna izango da, beraz. Aurrekarien atalean ikusi bezala ontologian oinarritutako neurriek psikologia eta adimen artifizialean egindako ikerketetan dute erroa, eta lan horiek dira erlazio-izaera berez aztertzen dituzten bakarrak, aplikazio konkretuetatik abstraituz.

Hiztegietako neurriak nahiko *ad hoc* dira. Corpusetarako teknika berak erabiltzen dira maiz (Wilks-enak kasu), baina badute corpusetako teknikek ez duten abantaila bat: hiztegietan kontzeptuak azaltzen dira, hitzaren adierak, eta hitz baten adieran azaltzen den informazioak adiera (kontzeptua) karakterizatzeko balio lezake. Hori da hain zuzen ere Lesk, Cowie, Véronis, Kozima eta Niwa-ren taldeen hurbilpenaren funtsa: adierei buruzko informazioa erabili erlazio-izaera formalizatzeko (Lesk, 1986; Cowie et al., 1992; Wilks et al., 1996; Véronis & Ide, 1990; Kozima & Furugori; Niwa & Nitta, 1994). Karov eta Edelmann-ek ere (1996; 1998) halatsu egiten dute, baina corpusa eta hiztegiko adierak lotzeko metodo bat planteatzen dute. Ez dugu esango hiztegian erlazio-izaerari buruzko informaziorik ez dagoenik, alderantziz, baina informazio hori era gordinean dago, egituratu gabe. Eta hori da hain zuzen ere Microsoft-eko taldearen ekarpena (Richardson, 1997), erlazio-izaera hiztegitik erauzitako Hiztegi-Ezagutza Base egituratu baten oinarrituta formalizatzea, eta ez zuzenean hiztegiko informazio gordina. Guk ere hiztegien ekarpena hor ikusten dugu, erlazio anitz erauzi ahal izateko potentziala duten gordailu bezala. Richardson-en lanean (1997) ez bezala, horrek ontologiak eta hiztegiak lotzea eskatzen du. Adierak eta kontzeptuak lotu behar dira, eta erlazioak hitzen artekoak baizik adiera/kontzeptuen artekoak izan behar dute. VI kapituluan helduko diogu gai horri, HEB batean adiera desanbiguazioa egin eta kanpoko ontologia bati lotzeari.

Corpusetako lanak dira zalantza gabe erlazio-izaeraren aplikazioetan emaitza onenak lortu dituztenak. Lengoaia Naturalaren Prozesamenduan asko ari dira hedatzen horrelakoak, eta nahiz eta batez ere lan enpirikoak izan, corpusen erabileraren inguruan ere eratzen ari da halako marko teoriko bat. Hala ere, kontzeptuen erlazio-izaera lantzean arazo garrantzitsuekin topatu ohi dira. Lehenbizikoa **adieraren definizio zuzenik ez** egotea da, ez dago kontzeptuenganako loturarik inon. Lan batzuek, horrela izanda, hitzen arteko erlazio-izaera besterik ez dute definitzen (Grefenstette, 1992; 1996; Grishman & Sterling, 1994; Lee, 1997; Golding & Schaves, 1996). Teoriaren aldetik kezkagarria bada, alderdi praktikoan ere arazoak ekartzen ditu, adieratara hedatu ahal izateko **eskuzko etiketatze semantikoa** eskatzen baitu (Church & Hanks, 1990; Hearst, 1991)[40]. Eskuzko etiketatzeak planteatzen duen arazo nagusiena denbora eta eskulan kopuruarena da, baina ez hori bakarrik, adieren mugak lausoak izaten baitira sarritan, eta giza-etiketatzaileen arteko ezadostasun maila nahiko altua da (%32koa Jorgensen-en arabera (1990)).

[40] Gale-ek eta (Gale et al. 1992; 1993; Yarowsky, 1993) adierak beste testuinguru baten definitzen dituzte, testu paraleloetan itzulpen ezberdinaren arabera. Horrela, aplikazio mugatu batentzat – itzulpen kontuetan – eskuzko desanbiguazioaren arazoa ekiditzen dute. Hala ere hau ezin izan dute orokortu beste adiera edo kontzeptuen definizioetara, eta arazo teorikoak hor dirau.

Corpusen inguruko hasierako proposamenei egindako hobekuntzak alor honetan izan dira batez ere: nola lortu eskuzko desanbiguaziotik alde egitea eta adierak euskarri trinkoago bati lotzea. Schütze-k (1992a; 1992b) hitzen agerpenak automatikoki multzokatzen ditu. Hearst berak eta Schütze-k (1993) WordNet-eko kategoriak multzokatu eta corpusetako hitzen agerpenak multzo horiei lotzen dizkie. Yarowsky-k (1992) adierak thesaurus bateko etiketa semantikoz bereizten ditu, baita ere automatikoki. Yarowsky berak, aurreragoko lanean (1994; 1995) beste hurbilpen bat hartu eta giza-anotazio lana errotik gutxituko duen algoritmoa plazaratzen du. Lan hauek guztiak norabide interesgarria edukita ere, ez dira heltzen adierei oinarri sendo bat ematera, eta batez ere ez dute lortzen hitzen agerpenak ontologiako kontzeptuei lotzea. Leacock-en azken lanean (Leacock et al., 1998) WordNet-en erabilera planteatzen dute eskuzko lana gutxitzeko. Ahalegin handiak eginda ere gaur egun eskuz etiketatutako adibide kopuru oso urria ikusita ez dirudi oraingoz corpusetan oinarritutako teknikak hitz gutxi batzuetatik harantzago joan ahal izango direnik.

Corpusetan oinarritutako lanek ere badute beste arazo bat, jadanik aipatutako **datu urrien arazoa** ikus III.A.3 atala). Arazo hori hitzak egitate isolatuak bezala aztertzetik dator, klase edo multzoak kontuan hartu gabe. Honek, nahiz eta paradoxiko iruditu, beste arazo bat ere sortzen du, **datu gehiegizkoen arazoa** deitu daitekeena. Alde batetik, datu urrien arazoa arintzeko ahal den corpus zabalenak erabiltzea komeni da. Bestetik, hitzen agerpen guztiak hartu behar dira kontuan erlazio-izaera behar den bezala aztertzeko. Hori dela eta hiztegiko hitz bakoitzarentzat bildu beharreko informazioa oso zabala da, eta hitz guztiena batzen badugu izugarria (ikus arazo honen adibide bat testu-zuzenketa automatikoan, V.D.3 atalean). Ziur aski hau da corpusen inguruko sistemak hitz multzo txikiekin[41] ebaluatu izatearen arrazoi nagusia. Bi arazo hauei erantzuten die Resnik-en lanak (1993a; 1993b; 1995; 1997), WordNet-eko klaseei corpusetan duten maiztasunari buruzko informazioa gehituaz, eta aditz eta objektuen arteko erlazio-izaera hitzez-hitz egin beharrean ontologiako kontzeptu eta klaseen arabera egiten den.

Hiztegietarako esan dugun bezala, corpusak ere informazio biltegi erraldoiak dira, baina bertan dagoen altxor hori, erabilgarria izanda ere, era egituratu batera erauzi beharra dago. Corpusetatik, beste inondik baino hobeto ziur aski, erraz atera daiteke urdaiazpiko eta sardexka hertsiki erlazionatuta daudela, baina ez litzateke nahikoa izan behar lotura horrek 0,967 indarra duela, erlazio beraren izaera ere lortu beharko litzateke. Horrela balitz, informazio esanguratsuena ontologiatan bildu zitekeen, modu konpaktuago batean, inferentzia mota ezberdinetarako integratuaz. Esandakoaren adibide bat da gorago aipatutako Resnik-en lana, aditzen hautapen-

[41] Yarowsky-k (1992) adibidez 8 hitzen gainean egiten du.

murrizpena WordNet-eko klaseen arabera deskribatzen baitu, hitzez-hitzeko informazioa laburbilduaz.

Ontologietan oinarritutako neurriak dira, beraz, teoria sendoena dutenak. Gainera adiera zer den garbi dago definitua, ontologiako kontzeptuen erreferentzien bidez. Ontologien arazoa, hala ere, eduki arazoa da. Ontologiaren diseinuan ezaugarri eta erlazio aberatsak egonda ere, beharrezko kontzeptu guztietan erlazio eta ezaugarri horiei balio bat ematea ez da makaleko lana. Eta ontologiak hiztegiaren zati garrantzitsua estaltzea ere beharrezkoa da. II. kapituluan aipatu dugu hau guztia, eta ikusi nola ontologia guztiek hiztegiaren estaldura arazoak dauzkaten. Hiztegi aldetik aberatsenetakoa WordNet da, baina honek erlazio gutxi dauzka landuta. Ontologietan oinarritutako erlazio-izaeren arazoa hori da, hain zuzen ere, ontologian dagoen informazioa besterik ezin dutela erabili (ikus horri buruzko iruzkinak III.F. atalean).

III.D.2. Dentsitatea eta ontologiatan oinarritutako beste teknikak

Tversky eta Quillian-en lanak interesgarriak izanda ere, erlazio-izaeraren inplementazio eraginkorra egiterakoan alde batera utzi izan dira. *Spreading activation* bitartez erlazio-izaera kalkulatzeko sare semantikoko[42] adabegi guztiak bisitatu behar dira, ez behin, baizik eta hainbat aldiz.

Radaren taldeak, sare semantikoen antolaketa kontuan hartuaz, beste erlazioak alde batera utzi eta erlazio paradigmatikoa soilik erabiltzea planteatu zuen, eraginkortasuna nabarmenki hobetuaz. Sussna izan zen lehenbizikoa Distantzia Kontzeptuala WordNet-en inplementatzen, bi kontzepturen arteko bideak erabiliaz. Erlazio paradigmatikoak soilik ez, eskura zituen meronimikoak ere erabili zituen, hobekuntza apala lortuaz bere esperimentuetan. Nahiz eta inplementazioak eraginkortasun arazorik ez eduki bi kontzepturen arteko distantzia bilatzeko (hierarkiaren batezbesteko sakonera bezainbat erlazio esploratu behar dira soilik, hau da ordena konstantea duen algoritmo batez –O(kte)– kalkulatu ahal da), lehen ikusi dugun bezala (III.B.2 atala) batez-beste M adiera dituzten N hitzen arteko distantziak kalkulatzeko $\frac{N\times(N-1)}{2}\times M^2$ aldiz bilatu behar da bidea. Honek $O(N^2)$ konplexutasuneko algoritmoa eskatzen du. Kontuan izanik autore batzuek 100 hitzetako leihoak darabilzkitela (adibidez adiera-desanbiguazioa egitean), arazo hau larria bihurtzen da.

Dentsitate Kontzeptualak, aldiz, beharrezko hitz guztien adieren arteko Dentsitatea behin kalkulatzen du, $N\times M$ adierak behin tratatuaz eta beraz konplexutasun apalagoko algoritmo bat onartuaz.

III.B.2 atalean aipatu bezala, binaka neurtzearen arazoa ez da praktikoa bakarrik, teorikoki ez dago oso argi N kontzepturen arteko binakako distantziak batzeak zer esan nahi duen, eta gainera ez da ageri modu errazik kopuru ezberdineko kontzeptu multzoen arteko distantziak konparatu ahal izateko. Dentsitateak aldiz edozein tamainako kontzeptu multzoen gertutasuna era natural batean neurtzeko neurria ematen du.

Dentsitatearen azterketarekin bukatzeko (emaitzen araberako ebaluazioa IV.C.3, V.D.3, VI.C.2 eta VI.D.9 ataletan jorratuko dugu), gogora ditzagun aldez aurretik jarri genizkion baldintzak:

1. Ontologiatan oinarritutakoa.
2. Adieren arteko neurria: ontologiako kontzeptuei erreferentzia egingo diena
3. Erlazio paradigmatiko eta sintagmatikoetako informazioa erabiliko duena
4. Kategoria irekietako hitzekin lan egingo duena
5. Eraginkorra izatea, testu zabalekin lan egin ahal izateko bezalakoa.
6. N kontzepturen arteko neurria izatea
7. Kontzeptu kopuru ezberdineko multzoen gertutasunak konparagarriak izatea.

Ezaugarri desiragarri hauetatik ikusi dugu Dentsitateak 1, 2, 5, 6 eta 7 betetzen dituela. 4. ezaugarriari dagokionean, Dentsitate Kontzeptuala izenekin besterik ez dugu probatu (ikusi IV., V.eta VI. kapituluak), baina ez dago eragozpenik beste kategoriatara hedatzeko. Ikustekoa da, noski, izenekin bezain emaitza onak lortu ahal izango direnik.

3. ezaugarriari buruz, II. kapituluan eta III.B.2 atalean ikusi izan dugu nola, gaur egun, ez dagoen hedadura zabaleko ontologiarik eskuragarri WordNet ez denik. WordNet-en arabera diseinatu da beraz Dentsitate Kontzeptuala, eta hala izan da erlazio hiperonimiko eta meronimikoak bakarrik erabiltzen dituela. Hau da, erlazio sintagmatikoetaz ez da baliatzen.

III.E. Ekarpena

Kapitulu honen helburu nagusia ezagutzan oinarritutako kontzeptuen arteko erlazio-izaera definitzea da, eta horretarako WordNet-en oinarritutako Dentsitate Kontzeptuala diseinatu eta inplementatu dugu.

Lehenbizi erlazio-izaera eta antzekotasunaren hainbat formalizazio aztertu ditugu, ezaugarri batzuen arabera. Hiztegi eta corpusetan oinarritutakoak interesgarriak izanda ere, oinarri teoriko sendoa dutenak ontologiatan oinarritutakoak direla arrazoitu dugu. Corpusen kasuan, emaitza oso onak

[42] Tesi honi dagokionean, sare semantikoak ontologia mota berezi bat bezala hartu ditzakegu.

lortuta ere adieraren definizio sendorik ez dagoela ikusi dugu, eta eskuzko desanbiguazioa ezinbestekoa dela sistemak adierak ezagutu ditzan. Gainera datu urrien eta datu gehiegizkoen arazoei aurre egin beharrean daude.

Hiztegi eta corpusetatik informazioa erauzteko beharra aitortzen dugu, eta garatutako erlazio-izaera espezifikoak horretan oso lagungarriak izango dira, baina defendatzen dugun ideia ontologia aberastearena da, ontologia aberats horretan lan egingo duen erlazio-izaera egokia definituaz. Laburbilduz ontologiek honako ezaugarriak eskaintzen dizkigute, besteen aurrean:

- Oinarri teoriko sendoa
- Adieren definizio sendoa
- Ez dute eskuzko desanbiguazio beharrik, ez eta datu urrien edo gehiegizkoen arazorik.

Ontologietan oinarritutako hauek eraginkortasun-arazoak dituzte. Gainera erlazio-izaeraren neurri guztiak bi kontzepturen artekoak, eta ez gehiago, izaten dira. Guk definitu dugun Dentsitate Kontzeptualak edozein kopurutako hitz multzoen erlazio-izaera kalkulatzeko gai da, konplexutasun apalagoarekin. Laburbilduz ezaugarri hauek dauzka Dentsitate Kontzeptualak:

1. <u>Ontologiatan</u> oinarritutakoa da.
2. <u>Adieren</u> arteko neurria da: ontologiako kontzeptuei erreferentzia egiten die.
3. Erlazio <u>paradigmatikoetako</u> informazioa erabiltzen du (hiperonimia eta meronimia).
4. <u>Izenekin</u> lan egiten du (aditzetarako ere egokia izan daiteke).
5. <u>Eraginkorra</u> da, testu zabalekin lan egin ahal izateko adinakoa.
6. <u>N kontzepturen</u> arteko neurria da.
7. Kontzeptu <u>kopuru ezberdineko</u> multzoen gertutasunak konparagarriak dira.

Dentsitate Kontzeptuala WordNet-en gainean inplementatu dugu, II. kapituluan arrazoitu bezala.

Erlazio-izaeraren neurri honek ez du eskatzen aurretiko inongo prestakuntzarik eta zeregin oso ezberdinetan aritu daiteke lanean, hurrengo kapituluetan ikusiko dugun bezala:

- Hitzen Adiera-Desanbiguazioa (IV. kapitulua)
- Testuen Zuzenketa Automatikoa (V. kapitulua)

- Ingelesa ez diren baliabide lexikal egituratuen eraikuntza sendotzeko (VI. kapitulua). Gure erabilera bikoitza da:
    - *Le Plus Petit Larousse* frantses hiztegiko adierak WordNet-i lotu
    - *Le Plus Petit Larousse*-etik erauzitako HEBko adieren hierarkiak desanbiguatu eta trinkotzea

III.F. Etorkizunerako lana

Dentsitate Kontzeptuala hobetzeko hiru alor nagusi hauek ikusten ditugu:

1. Darabilen informazioari dagokiona: erlazio sintagmatikoak dituen ontologia bat lortu edo WordNet erlazio sintagmatikoez aberastu.
2. Formulari dagokiona: Dentsitate Kontzeptualaren formula aldatu, bestelako erlazioak kontuan har ditzan.
3. Inplementazioari dagokiona: Inplementazioa azkartu.

Dentsitate Kontzeptualaren euskarri den WordNet ontologiak erlazio paradigmatikoak besterik ez dituenez, Dentsitate Kontzeptuala kalkulatzean ez da azaltzen erlazio sintagmatikorik. Informazio hori oso baliagarria izan daiteke erlazio-izaera neurtu ahal izateko: *baloia* eta *oina*, adibidez, oso urruti daude bata bestearengandik erlazio paradigmatikoak bakarrik erabiltzen baditugu, baina argi dago erlazio estua dagoela bien artean, beraien artean erlazio funtzional bat dagoelako eta ondorioz testuinguru berdinetan maiz azaltzen direlako. Arestian aipatu dugun bezala, hau da ontologia eta EBLek daukaten muga garrantzitsuetako bat, oso zaila baita halako informazioa eskuratzea.

Saiakerak egin dira, halere. Adibidez, ikus hautapen-murrizpenak corpusetatik ikasteari buruzko lanak (Grishman & Sterling, 1994; Ribas, 1995; Resnik, 1997). Corpusetatik adiera bakoitzak dauzkan kolokazioak ikasiz gero ere lagungarriak dira adieren arteko gertutasuna kalkulatzeko (Yarowsky, 1993; 1995). Hiztegi elektronikoetako definizioetatik agente, objektu eta antzeko erlazioak erauzi daitezke ere (Artola, 1993; Richardson, 1997). Topikoari buruzko informazioa ere interesgarria izan daiteke, Roget's tesaurusean edo LDOCE hiztegian azaltzen diren bezalakoak. Aurrekarien kapituluan azaldu ditugun informazio iturri guztiak izan daitezke baliagarriak.

Beraz, erlazio sintagmatiko horiek corpusetatik edo hiztegietatik erauzi daitezke, horien analisiaren bidez. Baliabide jakin batetatik erauzitako erlazioak baliabide horretako kontzeptu eta adieren artekoak izango direnez, WordNet aberasteko baliabide horiek bat egin beharko lirateke WordNet-ekin. Horrela WordNet-en integratuz joango lirateke corpus eta hiztegietatik erauzitako informazioa, edo bestelako ontologietan dauden erlazioak. Baliabide egituratuen bat egiteari buruz V. kapituluan arituko gara.

Nahiz eta erlazio paradigmatiko eta sintagmatikoak dituen ontologia eskura eduki, bai WordNet aberastuaz lortutakoa edo zuzenean eskuratutakoa, Dentsitate Kontzeptuala, hemen definitu dugun bezala, ez da gai informazio berri horretaz baliatzeko. Izan ere Dentsitate Kontzeptuala hierarkientzat dago pentsatuta, eta bestelako erlazioak integratzeko hedatu egin beharko zen. Erlazio sintagmatikoak erabiltzen dituzten erlazio-izaeren artean, (Agirre et al. 1994b)-ek LPPL-tik erauzitako erlazio paradigmatiko eta sintagmatikoak erabiltzen dituen Distantzia Kontzeptualerako proposamena egiten du. (Mahesh et al. 1997)-ek Mikrokosmos ontologiarekin eta Richardson-ek (1997) hiztegietatik erauzitako HEBarekin ere egiten dute beraien proposamen propioa.

Azkenik, nahiz eta Dentsitate Kontzeptualaren algoritmoa konplexutasun gehiegizkoa ez izan, inplementazio azkarragoa lor daitekeela uste dugu. Horren arrazoietako bat LISP lengoaiaz inplementatuta egotea da, eta bestea WordNet-eko informazioaren atzipena ez dagoela optimizatuta. Egun, C++ lengoaiaz inplementatutako bertsio bat lantzen ari gara, UNED-eko Elektrizitate eta Elektronika saileko ikerkuntza taldearekin batera, ITEM[43] proiektuaren barruan. Bertsio hau ingeniaritza linguistikorako GATE[44] ingurunearen barruan (Cunningham et al. 1997) integratuta egongo da laster.

[43] http://sensei.ieec.uned.es/item/

[44] http://www.dcs.shef.ac.uk/research/groups/nlp/gate/

IV. Kapitulua

HITZEN ADIERA-DESANBIGUAZIOA TESTU ERREALETAN

Kapitulu honetan Dentsitate Kontzeptualaren ebaluazio praktikoa egin nahi izan da, aplikazio bezala Hitzen Adiera-Desanbiguazioa (HAD) erabiliz. Horretaz gain Dentsitate Kontzeptualaren parametro batzuk finkatzea ere nahi izan dugu. Hasteko hitzen adiera-desanbiguazioari buruzko sarrera egingo dugu eta aurrekariak aztertu. IV.B. atalean esperimentuaren diseinua azalduko dugu. Ondoren Dentsitate Kontzeptuala erabiltzen duen algoritmo desanbiguatzailea aurkeztuko dugu, eta ebaluazioari buruz ihardun aurretik Dentsitatearen parametroak doituko ditugu. IV.D. atalean beste metodoen emaitzekin konparatuko dugu gurea, eta bukatzeko kapitulu honetako ekarpenak aipatuko ditugu.

IV.A. Sarrera eta aurrekariak

HADaren garrantziari buruz honakoa zioen Hirst-ek (1987: 5 or.): "*Any practical Natural Language Understanding system must be able to disambiguate words with multiple meanings, and the method used to do this must necessarily work with the methods of semantic interpretation and knowledge representation used in the system.*". Duela gutxi argitaratutako HADaren egungo egoeraren azterketan Ide eta Véronis (1998) ere uste berekoak dira: "*Sense disambiguation is an intermediate task, which is not an end in itself, but rather necessary at one level or another to accomplish most natural language processing tasks. It is obviously essential for language understanding applications, …*". Lengoaia naturalaren ulermenerako soilik ez ordea, HADaren ekarpena oinarrizkoa da beste aplikazio askok eraginkortasuna lortu dezaten, hala nola, itzulpen automatikoa, informazioaren berreskuratzea, dokumentuen berreskuratze eta sailkapena, analisi sintaktikoan bertan, testu eta mintzairaren prozesamenduan, etab.

Azken urte hauetan HAD bigarren maila batetatik Lengoaia Naturalaren Prozesamenduaren lehentasunezko arazo izatera pasatu da berriz ere. HADaren berezko zailtasuna Bar-Hillel-en (1960) itzulpen automatikoari buruzko tratatu ezagunean puntu nagusia zen. Bere argumentuek ALPAC (1966) txostenaren oinarria izan ziren, hain zuzen ere 60. hamarkadan itzulpen automatikoaren finantzaketaren beherakada ekarri omen zuena. Adimen artifizialean oinarritutako desanbiguazio sistemak aro horretan hasi ziren zabaltzen, baina beti ere arrakasta apalarekin. Orduko desanbiguatzaileak hitz anbiguo aldrebesekin frogatu ohi ziren, esaldi gutxi batzuetako agerpenak aztertuaz. Azken hamarkada honetan, ordenadorez atzitu daitekeen testu kopuru zabalak bultzada eman die datuetan oinarritutako teknikei, emaitza deigarriak lortuaz testu errealetan. Hori dela eta HADak inoiz baino arreta gehiago jaso izan du (adibidez, HADari buruzko 171 artikulu dauzkagu jasota, horietatik 161 90. hamarkadan argitaratuak), eta gaur egungo lengoaia naturalaren prozesamenduak duen arazo nagusienetako bezala aipatu izaten da.

Adimen artifizialaren inguruko ikerlariek, baita LNPko buru gehienek ere, HAD arazoa *AI-complete* dela uste dute, hau da, konpondu ahal izateko lehenbizi adimen artifizialeko arazo gaitz guztiak, sen ona eta ezagutza entziklopedikoaren errepresentazioa barne, ebatzi beharko lirateke. Gaur egun, ordea, eta aurreko baieztapenari arrazoia kendu gabe ere, HAD teknologia heltzen ari dela usten dutenak ugaltzen doaz, eta testu libreetako hitz gehienentzat adiera egokiena topatzea eskura dugula aditzera eman nahi dute, nahiz eta modu ez-perfektu batez izan, hainbat aplikaziotan erabilgarria izateko modura.

HADak hartu duen garrantzia dela eta, honen inguruko lanak asko ugaldu dira. Horien azterketari ekin baino lehen HADaren karakterizazio bat egingo dugu. Bi pauso nagusi ezberdindu ohi dira (Ide & Véronis, 1998):

1. hitzek dauzkaten **adieren zehaztapena**.
2. hitz bakoitzaren agerpenari **adiera bat esleitzeko metodoa**.

Adieraren definizio zehatza zein den Aristotelerengandik hasi eta egun arte erabaki gabeko eztabaidaren gunea da. Hori horrela izanda, autore batzuek (ikusi adibidez Kilgarriff, 1997a) adierak zerrendatu beharko liratekeen ere zalantzan jartzen dute, eta beraien kritikek filosofia, psikologia eta linguistikan erro sendoak dituzte. Kritikak kritika izanda ere, **adiera-zerrendak** dira nagusi ikerkuntza arlo honetan, eta lan gehienak aurrez emandako adieratan oinarritzen dira, hurrengo eratakoak barne:

- adieren zerrenda (hiztegietan aurkitu daitekeenaren antzekoa)
- ezaugarri multzoa (adibidez, corpusetatik ateratako testuinguru-ezaugarriak)
- beste hizkuntza baterako itzulpenen zerrenda

Hitz baten agerpena desanbiguatzean hainbat ezagutza-iturritara jotzen da, baina nagusienak horrela sailkatu ditzakegu:

- desanbiguatu behar den hitzaren **agerpenaren testuingurua**: testua, diskurtsoa, informazio extra-linguistikoa, etab.
- kanpoko ezagutza iturriak: **baliabide lexikal edo entzilopedikoak**, eskuz sortutako ontologiak, etab.

Desanbiguazio lan orok zera eskatzen du, hitzaren agerpenaren testuingurua kanpoko ezagutza iturriko informazioarekin edo lehenago corpusetan desanbiguatutako hitzaren beste agerpenetatik eratorritako informazioarekin ezkontzea Bata edo bestea aukeratzeak sortzen du HADan dauden bi familia nagusien arteko bereizketa: **ezagutzan oinarritutako HAD** edo **datuetan oinarritutako HAD**. Adierari buruzko informazioa agerpenarekin ezkontzean asoziazio metodoak erabiltzen dira batez ere, aurreko kapituluan aipatutako erlazio-izaerak hain zuzen ere (ikusi III.A atala)

Erlazio-izaeraren garrantzia HADan bistakoa da, erlazio-izaeraren formalizazio askoren motibazioa HAD bera da eta. Aurrekarien azterketan ikusiko dugun bezala, HADaren hurbilpen askotan erlazio-izaera hutsa erabiltzen da adiera aukeratzeko, nahiz eta lan teorikoenek beste teknika eta informazio iturriak beharrezkoak direla planteatu, orain ikusiko dugun bezala. Beraz, ezagutzan oinarritutako HAD lanek ontologia zein hiztegiz baliatutako erlazio-izaera darabilte, eta datuetan oinarritutako HAD sistemak corpusetan errotutako erlazio-izaera neurriak. Beheko IV.A.1. atalean azalduko dugu nola erabili daitekeen erlazio-izaera HADrako.

Aurrekarien azterketa hasi aurretik hitz bi anbiguetate lexikalaren inguruan. Hiru mota bereizi izan dira anbiguetate lexikalean: polisemia (adieren esanahia erlazionatuta dago), homonimia (adieren artean ez dago erlaziorik) eta kategoriazko anbiguetatea (adierak kategoria ezberdinekoak dira). Kategoriazko anbiguetatea garrantzitsua izanda ere, albo batera utzi ohi da, ezagutza sintaktiko hutsez erraz ebatzi ohi da eta. Homonimia eta polisemia inguruan ez da normalean bereizketarik egiten, ez bada sistema batzuk homonimia mailako anbiguetatea bakarrik kontuan hartzen dutelako. Hirst-ek (1987) hala zioen polisemia eta homonimiaren arteko bereizketaren inguruan: "*The semantic objects we will be using are discrete entities, and if a word maps to more than one such entity, it will generally (but not always) be a matter of indifference how closely related those two entities are.*". Gainera polisemia, homonimia eta metaforen artean ez dago muga garbirik; alde batetik polisemia eta homonimia arteko ezberdintasuna oso erlatiboa da, subjektiboa, eta bestalde urteak pasa ahala metafora lexikalizatu egin daiteke, homonimia edo polisemia emanaz. Metaforaren tratamendua, dena den, lan honen esparrutik kanpo dago.

Aurrekarien azterketa, aurreko kapituluan bezala, ezagutza iturriaren arabera antolatu dugu: ontologiak, hiztegiak, corpusak eta konbinazioak. HADaren inguruko azterketa bibliografiko sakona egitea gehiegizkoa litzateke hemen, eta aurreko kapituluan aurkeztutako lanak azalduko zaizkigu hemen bereziki. Lanetako gehienek ezagutza iturri bakarra lantzen dute, halakoarekin desanbiguazio onargarria lortu daitekeelakoan. Horiek aztertu baino lehen aipatu ditzagun HAD ikuspuntu orokorrago batetik aztertu izan dituzten oraintsuko lan bi.

IV.A.1. Beharrezko diren ezagutza iturriak

Adimen Artifizialean oinarritutako hurbilpenak dira, zalantza gabe, desanbiguazioan parte hartzen duten faktoreak sakon aztertu eta desanbiguatzeko beharrezkoak diren informazio iturriak bereizi dituztenak. Hirst-ek (1987) adibidez diskurtsoaren testuingurua eta esaldiko bertako pistak kontuan hartu beharrekoak zirela uste zuen[45]. Alde batetik diskurtsoaren testuingurua finkatzea lortuz gero (testuaren domeinu eta topikoa) hitzaren adiera bakarra izan daiteke egokia testuinguru horrentzat. Bestetik, esaldian bertan dauden pistak nahikoak izan daitezke adiera bereizteko, hara nola esaldiko hitzen adieren arteko erlazio-izaera (Quillian 1968), pista sintaktikoak, edo hautapen-murrizpenak. Dena den, badaude hainbat kasu goi mailako inferentzia (sen ona) eskatzen dutenak adiera hautatu ahal izateko.

McRoy-k (1992), oraintsuagoko lanean, ezagutzan oinarritutako sistema batek kontuan hartu beharko lituzkeen ezaugarri eta ezagutza motak zerrendatzen ditu:

- hitzaren morfologia
- testuinguruari egokitzen zaion hitzaren kategoria
- domeinu edo maiztasunaren arabera, zein adiera diren egokiagoak

- ea hitza kolokazioren bateko parte den, adibidez *soda cracker* edo *take action*
- testuinguruak adieraren bat nahiago duen: testuinguruko beste adierekin topiko, egoera edo kategoria semantikoari dagokionez harremanik duen
- ea adierek dauzkaten baldintza sintaktikoak testuinguruan betetzen diren
- ea hautapen-murrizpenak betetzen diren
- ea adiera diskurtsoan indarrean dagoen zerbaiti lotuta dagoen

Guzti horietatik ordea, garrantzitsu edo emankorrenak hauek direla deritzo: adieren kategoria bera (kategoriazko anbiguetatea ebazteko), morfologia (adibidez *agreement*-en *agree*-ren adieretatik 3 bakarrik dira egokiak eratorpen horretan), kolokazio eta hitzen arteko asoziazioak (adibidez, *bank/money* elkarrekin azaltzea edo *increase in* orduan *in* hori normalean ekintzaren pazienteari dagokio eta ez akzioaren leku edo norabidea). Hautapen-murrizpenak ere garrantzitsuak direla dio, baina bigarren mailan.

Hirst eta McRoy-k aipatutako ezagutza iturriak laburbilduz gero:

1. adieraren agerpenaren kategoria
2. morfologia
3. pista sintaktikoak eta kolokazioak maneiatzeko mekanismoa
4. hautapen-murrizpenak betetzen diren erabakitzeko mekanismoa
5. inguruan dauden hitzen arteko harremanak bilatzeko mekanismoa
6. testuinguruaren ezagutza (topiko eta domeinua)
7. inferentzia orokorra, azken irtenbide bezala

Esan bezala, kategoriazko anbiguetatea ebatzita dago, gaur egun dauden kategoria etiketatzaileen eraginkortasunari esker. Egile gutxik aitortzen dute, bestalde, morfologiaren garrantzia, aplikazio gehienetan hitzaren barruko egitura ez delako interesgarria, nahikoa lan dute hitz osoaren adiera erabakitzen. Literaturako lanetan nekez topatzen dira inferentzia orokorraren ekarpenari buruzkoak ere. Onartu izaten da desanbiguazio osoa lortzeko beharrezkoa dela, baina ezaguna da ordenadoreen sen ona ez dela oraingoz inondik inora ageri. Gehien azaltzen diren ezagutza iturriak, beraz, 3.etik 6.era doazenak dira.

[45] "*For an NLU system to be able to disambiguate words, it is necessary that it use both the discourse context in which the word occurs and local cues within the sentence itself*." (Hirst, 1987; 6. or.)

Hirst eta McRoy-ren aipaturiko lanetan ez bezala, ordea, gehienetan ezagutza iturri horiek ez dira modu bereizi baten azaltzen. Izan ere ezagutza iturri horiek ez daude eskuragarri, eta beraien erauzketa eta eraikuntza LNParen arazo estuenetako bat da. Horregatik beharbada, lan gehienetan ezagutza iturri bakarra erabili ohi izaten da, corpus, hiztegi edo ontologietan oinarritutako erlazio-izaeraren neurriren bat (ikusi 7. taula).

3.	pista sintaktikoak eta kolokazioak:	adierei buruzko ezagutza sintaktikoa
4.	hautapen-murrizpenak:	erlazio sintagmatiko lokala, paradigmatikoaz konbinatuaz
5.	hitzen arteko harremanak:	erlazio sintagmatiko lokal, global eta paradigmatikoa
6.	topiko eta domeinua:	erlazio sintagmatiko global eta paradigmatikoa

7. taula: desanbiguatzeko beharrezko ezagutza eta erlazio-izaeraren arteko harremana

Erlazio-izaeraren bidez modelatzen ez den ezagutza mota bakarra pista sintaktikoak eta kolokazioak dira. Horien garrantzia esperimentalki frogatu izan da, eta emaitza hoberenak lortu dituzten sistemak erlazio-izaerekin integratu izan dituzte (ikusi IV.A.4. atala).

IV.A.2. Ontologiatan oinarritutako HAD

Arestian aipatutako bi lanak (Hirst, 1987; McRoy, 1992) Adimen Artifizialean oinarritutako hurbilpenen adibide tipikoak dira. Alde batetik adierak zer diren definitzeko ontologiako kontzeptuetara jotzen dute, eta hala hitz bat anbiguotzat joko da ontologiako kontzeptu bati baino gehiagori egiten badio erreferentzia. Adierak, beraz, adiera-zerrenda baten bidez definitzen dira. Bestalde, nahiz eta potentzialki anbiguetate korapilatsuak ebazteko prestatuak egon, praktikan, ontologian dagoen informazio murritza dela eta, adibide gutxi batzuekin besterik ez dira probatu izan. Bi lan horietan ebaluazioa era abstraktuan egin izan da, inongo emaitza enpirikorik azaldu gabe.

Sussna-k (1993) bai ebaluatzen duela ontologiatan oinarritutako bere sistema, informazioa iturri bakarrera murriztearen truke: WordNet-eko ezagutza paradigmatikoa. Distantzia Kontzeptualaren bidez lortzen dituen emaitzak ez ditu zuzenean konparatzeko moduan ematen, baina 8. taulan azaltzen den doitasuna kalkulatu diogu, gutxi gora behera. IV.D atalean lasaiago ebaluatuko dugu, gure hurbilpenaren antzekoa da eta. WordNet erabiltzen duten lan gehiago ere badaude, eta horietako batzuk IV.A.5. atalean ikusiko ditugu, ezagutza iturri gehiago konbinatzen baitituzte.

Mahesh-ek eta ontologian bertan errepresentatzen dute hautapen-murrizpena. Izenen adierak desanbiguatzeko hautapen-murrizpenak eta ontologiako kontzeptuen adieren arteko hurbiltasuna nahiko direla defendatzen dute, baina nahiz eta ondo arrazonatu, ezin dute zenbakizko daturik eman, beraien Mikrokosmos ezagutza-basearen estaldura urria delako.

Aurreko kapituluan aipatu ziren atal honetako lan batzuk ez ditugu hemen aipatu, HADan erabili ez direlako. Berdin gertatuko da beste sailetan ere.

	Erlazioak			Adierak		Ebaluzioa			
	Par	Lok	Gl	Jatorria	Granularitatea:	Kop.	Kat.	Est.	Doi.
Hirst, 1987	X	X	X	Ontologia	Polisemia	-	-	-	-
McRoy, 1992	X	X	X	Ontologia	Polisemia	-	-	-	-
Sussna, 1993	X			WordNet	Polisemia	~1000	Izena	?	~%47
Mahesh et al., 1997	X	X		Mikrokosmos	Polisemia	-	-	-	-

8. taula: ontologian oinarritutako lanen sinopsia[46]

IV.A.3. Hiztegietan oinarritutako HAD

Hiztegietan oinarritutako sistemetan adiera zerrendak erabiltzen dira adierak definitzeko, noski. Erlazio sintagmatiko globalean oinarritutako erlazio-izaera erabiltzen da. Lesk-en hasierako proposamenaren hedadura ezberdinek antzeko emaitzak lortzen dituzte: %50 baino gutxiago polisemia mailan eta %70 inguru homonimia mailan (ikusi 9. taula). Aipatu beharra dago Véronis eta Ide-ren kasuan (baita Niwa eta Nitta-renean ere) emaitzak ematerakoan erabilitako irizpideak ez daudela batere garbi.

	Ezagutza			Adierak		Ebaluazioa			
	Par	Lok	Gl	Jatorria[47]	Granularitatea	Kop.[48]	Kat.	Est.	Doi.
Lesk, 1986			X	W7 OALDCE CED	Polisemia	2 testu	denak	?	%50-%70
Cowie et al., 1992			X	LDOCE	Polisemia	50 esaldi	denak	?	%47
					Homografia				%72
Véronis & Ide, 1990			X	CED	?	?	?	?	%72
Niwa & Nitta, 1994			X	CED	Domeinua (2 adiera)	9x20 hitz	izenak	?	~%75
Wilks et al., 1990			X	LDOCE	Polisemia	1x197 hitz	izenak	100%	%45
					Homografia				%90

9. taula: hiztegietan oinarritutako lanen sinopsia

46 Taulako eremuen esanahia:
Erlazioak: paradigmatiko, sintagmatiko lokala eta sintagmatiko globala.
Adierak: adieren jatorria eta granularitatea, bereizketa xehea (polisemia) edo zabala (homonimia, homografia edo domeinua).
Ebaluazioa: zenbat hitzekin egin den, hitzen kategoria, emaitzen estaldura eta doitasuna (~ ikurrak gutxi gora bera esan nahi du).

47 Laburduren esanahia: CED *Collins COBUILD English Language Dictionary* (Sinclair, 1987), W7 *Webster's Seventh New Collegiate Edition* (Gove, 1969), OALDCE *Oxford Advanced Learner's Dictionary of Current English* (Hornby, 1974), LDOCE *Longman's Dictionary of Contemporary English* (Procter, 1978).

48 9x20 hitz azaltzen denean, 9 hitz aukeratu eta horietako bakoitzaren 20 agerpen desanbiguatu direla adierazi nahi da.

IV.A.4. Corpusetan oinarritutakoak

Adierak espezifikatzeko adiera-zerrendak erabiltzen dira batez ere, eta horrek corpusetan adieren etiketak eskuz jarri beharra suposatzen du. Tamalez, adieraz etiketatutako corpusak oso urriak dira, eta beraz metodo hauen etsai amorratuena eskuzko desanbiguazioaren beharra da. 10. taulan zutabe bat gehitu dugu honen inguruko beharra argitzeko.

Lan gehienetan arazo horri ebazpenak bilatzen saiatzen dira. Beherago aurkeztuko ditugun Hearst (1991) eta Yarowsky (1995), adibidez, hitz etiketatu urrietatik ikasten ahalegintzen dira, eskuzko lana gutxitu ahal izateko. Schütze-k beste bide bat bilatzen du, eta lehenbizi hitzaren agerpenak automatikoki multzokatu, eta gero adiera-etiketa jartzen die, multzo guztiari batera. Gale, Church eta Yarowsky-k, bestalde, adiera-zerrenden hurbilpena alde batera utzi eta adierak beste era batera espezifikatzea proposatzen dute: hitz batek adiera ezberdinak ditu beste hizkuntza baten itzulpen ezberdinak baditu. Honen abantaila zera da, corpus elebidunetatik automatikoki etiketatu daitezkeela hitzen adierak (itzulpen ezberdinak) eskuzko lana erabat saihestuz. Tamalez, gaur egun corpus elebidunak oso urriak eta gai espezifikoei buruzkoak dira.

Erabiltzen den informazioaren inguruan, bi korronte nagusi egon dira: alde batetik pista sintaktiko eta kolokazioak soilik erabiltzen dituztenak (Hearst, 1991), eta bestetik erlazio sintagmatikoan oinarritutako erlazio-izaera soilik erabili izan dituztenak (Gale et al., 1992; 1993; Schütze 1992a; 1992b; ikus III.A.3 atala). Lehenbizikoen kasuan, hitzaren adiera bakoitza agertzen den testuinguru sintaktikoa aztertu ohi da, eta bigarrenean bai esaldi eta bai diskurtsoan zein hitzekin azaldu ohi den. Inplementatzeko orduan, lehenbizikoan adieraren inguruko ±2 zabalerako leihoan dauden hitz eta kategoriak hartzen dituzte kontuan (kolokazio eta pista sintaktikoak bildu nahian), orden eta posizioari buruzko informazioa kontuan hartuaz, eta bigarrenenean leiho zabalagoetan (±50) azaltzen diren izen, adjektibo eta aditzak, ordena eta posizioari buruzko informazio gabe (erlazio-izaera sintagmatiko lokal eta globala neurtu nahian). Emaitzei dagokionez, bata edo besteaz soilik baliatzen direnak %90 doitasunaren inguruan dabiltza (ikusi 10. taula).

Hearst-ek (1991), adibidez, , analisi sintaktiko oso azaleko batetik abiatu (kategoria-etiketak eta sintagma sinpleen mugak) eta adieraren testuinguruan dauden pista sintaktikoak (hitzaren ezker/eskuinean kategoria zehatz bat egotea, ezker/eskuinean preposizio jakin bat egotea, etab.) aztertzen ditu. Adiera bakoitzarentzat eskuz etiketatuko corpusetik ezaugarri sintaktiko horiek erauzi, eta hitz bat desanbiguatzerakoan ezaugarri horiek hitzaren testuinguruarekin konparatu eta adiera egokiena aukeratzen du. Eskuzko etiketatze lana aurrezte aldera algoritmo lagungarri bat ere aurkezten du.

Nahiz eta ikertzaile askok bere hurbilpenaren onurak defendatu beste batzuek bien beharra aitortzen dute[49]. Horrek estatistika alorreko arazo teorikoak planteatzen ditu, iturri ezberdineko ebidentzia ez independenteak (erlazio-izaera sintagmatikoari dagozkionak, pista sintaktikoak eta kolokazioak) konbinatzeari dagokionean.

Yarowsky-k (1993; 1994; 1995) erlazio sintagmatikoan oinarritutako erlazio-izaera (Gale et al. 1992; 1993) hedatu eta Hearst-en antzeko pista sintaktiko eta kolokazioak ere kontuan hartzen ditu[50], emaitzak hobetuaz. Bi ezagutza iturriak integratzean ez ditu ebidentzia guztiak konbinatuko, eta ebidentzia indartsuena bakarrik aukeratuko du (erabaki-zerrenda edo *decision list* direlakoak erabiliz). 1995ko lanean eskuzko lana gutxitu ahal izateko metodo iteratibo bat ere azaltzen du. Ebidentziak konbinatzeko beste modu bat erabiliaz Towell eta Voorhees-ek (1998) erabaki zerrendak baino sare neuronalak darabiltzate, emaitza onekin. Izenetarako lana adjektibo eta aditzetara zabaltzen dute, baina tamalez kategoria bakoitzeko hitz bakarra probatuz.

Aipatu behar da corpusen inguruko lan gehienetan, hemen aipatutakoak barne, ez direla testu bateko hitz guztiak desanbiguatzen ahalegintzen, eta ebaluazioa hautatuko hitz gutxi batzuen agerpenak erabiliaz egiten dute. Bestalde, bi adiera besterik ez direla bereizten, bata bestearengandik oso ezberdinak eta maiz topiko ezberdinetakoak. Salbuespen bakarra Towell eta Voorhees-en lana da, WordNet-eko adierak erabiltzen dituzte eta. Probatutako hiru hitzen adiera kopurua kontuan hartuta (sei, hiru eta lau) oso emaitza onak lortzen dituztela esan daiteke[51].

Niwa eta Nitta (1994) aipatzen ditugu berriro hemen, corpusen kookurrentzietan oinarritutako bektoreen bidez lortutako emaitzak hiztegietako emaitzekin alderatzen dituzte eta (konparatu 9. eta 10. tauletako doitasunak).

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[49] Hala dio Schützek (1992[a]): "*The disambiguation algorithm presented doesn't use any information that is encoded in the order of words and ignores morphology and function words. … Future research has to be done on how the method can be extended to include a wider range of linguistic phenomena*".

[50] Adieren testuinguru sintaktikoaren eredu bezala ezker/eskuinera dauden hitz eta kategoriak soilik hartuko ditu kontuan soilik.

[51] Hala ere ez dituzte WordNet-en dauden adiera guztiak erabiltzen, izan ere erabilitako hitzentzat WordNet-ek 27, 13 eta 29 adiera dauzka eta. Horregatik azaltzen da granularitateari buruzko zutabean ~ ikurra.

	Ezagutza mota				Adierak		Ebaluazioa				Lana eskuz
	Par	Lok	Gl	Sx	Jatorria:	Granularitatea	Kop.	Kat.	Est	Doi	
Gale et al., 1993		X	X		Itzulpena	Domeinua (2 adiera)	6	Izenak	%100	>%90	ez
Schütze, 1992		X	X		Multzokatzea +eskuz	~Homonimia	4x200	Izenak	%100	>%90	dezente
Hearst, 1991				X	Eskuz	Homografo (2 adiera)	4x30	Izenak	%100	~%90	dezente
Yarowsky 1995		X	X	X	Eskuz, itzulpena	~Homonimia (2 adiera)	10x4000	Izenak	%100	~%97	gutxi
Towell & Voorhess, 1998		X	X	X	Eskuz, WordNet	~Polisemia	3x350	Izen, adj. eta aditzak	%100	~%86	dezente
Niwa & Nitta, 1994		X	X		Eskuz, Roget's	Domeinua (2 adiera)	9x20	Izenak	?	~%85	asko

10. taula: corpusetan oinarritutako lanen sinopsia

IV.A.5. Konbinatutako HAD

Atal honetako sistemak corpusetan oinarritutako hedaduratatik datoz batez ere, eta eskuzko desanbiguazioa eta datu urrien arazoa gutxitzea dute helburu, bide batez hitzen adierak definitzeko helduleku sendoago bat ezarriaz. Aurreko kapituluko III.A.4 atalean aurkeztutako lanetaz aparte, Leacock, Chodorow eta Miller-ek (1998) pista sintaktikoak eta erlazio sintagmatikoa ere erabiltzen dituen sistema aurkezten dute. Lan honen berrikuntza, ordea, eskuzko desanbiguazioa saihesteko sistema da: adiera baten adibideak lortzeko, WordNet erabiliaz adiera horren sinonimoak aztertu eta horietako bat momosemikoa bada, orduan sinonimo hori azaltzen den testuinguruak adiera beraren testuinguru bezala jotzen dira.

Emaitzei dagokionez, alde nabariena adiera bereizketa zabal edo finen artean dago berriz ere. Bereizketa zabala egiten dutenen artean %90eko emaitzak lortzera heltzen dira. WordNet-ek egiten dituen bezalako adiera bereizketa finentzat desanbiguatzean, ordea, %40 inguruko doitasuna aipatzen du Resnik-ek. Tartean leudeke Leacock-ek eta lortutako emaitzak (%80 inguru), Towell eta Voorhees-en (1998) kasuan bezala ez baitute adiera WordNet-en xehetasun osoz bereizten.

	Ezagutza				Adierak		Esperimetua				Lana eskuz
	Par	Lok	Gl	Sx	Jatorria	Granularitatea	Kop.	Kat.	Est.	Doi.	
Yarowsky 1992			X		Roget's	Domeinua (2 adiera)	12 x asko	Izenak	%100	~%92	ez
Resnik 1997,	X				WordNet	Polisemia	Asko	Izenak	?	~%40	ez
Hearst & Schütze, 1993			X		WordNet	Domeinua	-	-	-	-	ez
Karov & Edelmann 1996			X		Eskuz	Domeinua (2 adiera)	4x125	Izenak	%100	>%90	ez
Leacock et al., 1998		X	X	X	WordNet	~Polisemia	14 x asko	Denak	%100	~%80	ez

11. taula: konbinatutako lanen sinopsia

IV.B. Ebaluaziorako esperimentuaren diseinua

Azken urteotako salbuespen batzuk kenduta, orain arteko lan gehienek (eta corpusean oinarritutakoen kasuan, guztiek) hitz kopuru mugatu batekin lan egin izan dute. Hori dela eta ez da inolaz frogatu corpusetan oinarritutako adiera desanbiguatzaileak, emaitza onenak eskaintzen dituztenak izanda ere, hitz konkretu batzuk desanbiguatzetik testu orokorrak desanbiguatzera pasatu daitezkeenik. Aipatzekoa da, baita ere, emaitza arrakastatsuenek bi adiera oso bereizi artean besterik ez dutela desanbiguatu izan. Adieren granularitatea hain ezberdina izatean, oso zaila da sistema ezberdinen arteko emaitzak konparatzea.

Arrazoi horiengatik, sistemen artean konparatu ahal izateko, esperimentua horrela diseinatu genuen:

1. Ausaz aukeratutako testu osoak desanbiguatu.
2. Domeinu publikoan dauden testu etiketatuak erabili.
3. Domeinu publikoan dagoen adiera espezifikazioa erabili.

Azken bi puntuak betetzen dituen corpusa aipatu dugu jada: SemCor (ikusi II. atala). Semcor domeinu publikoan dago, eta WordNet-eko adieraz dago etiketatuta. WordNet erabiliko da adiera espezifikazioentzat, eta testu sorta osoak etiketatu beharko dira. HADan WordNet erabiltzearen kontrakoak ere badaude, egiten diren adiera bereizketak xeheegiak direla eta. Hori dela eta, adieraren bi maila definituko ditugu: WordNet-eko adiera bera, eta adieren bereizketa zabalagoa egin ahal izateko, adieren etiketa semantikoa (ikusi IV.C.3 ebaluazioaren atala).

Literaturako lan gehienenetan bezala, izenekin egingo dugu ebaluazioa, baina gure kasuan testuan agertzen diren izen guztiekin. SemCor-eko lau fitxategi aukeratu genituen ausaz (ikusi 12. taula). Fitxategian testu ezberdinetatik hartutako puskak egon daitezke. Fitxategi bakoitza genero ezberdin batekoa suertatu zen: br-a01 delakoa "Press:Reportage" bezala zegoen sailkatua, br-b20 "Press:Editorial", br-j09 "Learned:Science" eta azkenik br-r05 "Humour" bezala. Fitxategietako izenen %11 ez zegoen WordNet-en. WordNet-en topatutako izenetatik %32 adiera bakarrekoa zen.

SemCor-eko fitxategiak WordNet-eko adieraz etiketatuta daude, eta hortaz automatikoki ebaluatu daiteke desanbiguatzean lortutako emaitza zein den, desanbiguatzailearen erabakia SemCor-en dagoenarekin konparatuaz. Ebaluazioa horrela egiteak adiera zuzen bakarra onartzea dakar, hau da, nahiz eta sistemak aukeratutako adiera eta SemCor-ekoa ia berdinak izan, ebaluazioari dagokionez txartzat joko da.

testuak	hitzak	izenak	WNen dauden izenak	izen monosemikoak
br-a01	2079	564	464	149
br-b20	2153	453	377	128
br-j09	2495	620	586	205
br-r05	2407	457	431	120
guztira	9134	2094	1858 (%89)	602 (32%)

12. taula: esperimentuko testuen datuak

IV.C. HAD Dentsitate Kontzeptuala erabiliaz

Gure hurbilpenean garbi geneukan ontologia eta erlazio-izaera orokor baten gainean oinarritu beharra zegoela, eta WordNet izango zela gure erreferentzia ontologikoa (guzti honen justifikaziorako jo III.D atalera). Hurbilpen honek adieraren definizio sendo bati heltzen dio, eta corpusetan oinarritutako tekniken arazorik ez du, hala nola eskuzko desanbiguazioaren beharrik edo datu urrien arazorik.

HADaren lan teorikoen ildoa jarraituz (ikus kapitulu honetako IV.A.1 atala), ez dugu uste ezagutza mota bakarra nahikoa denik desanbiguazio zorrotza lortzeko, ezta WordNet-en daudenik beharrezko erlazio mota guztiak[52]. Bestalde, WordNet-en oinarritutako Dentsitate Kontzeptuala desanbiguaziorako erabilgarria dela frogatu nahi dugu, eta adiera-desanbiguazio sistema arrakastatsu baten oinarrizko osagaia, erlazio-izaera paradigmatikoa formalizatzen duena.

Kapitulu honetan aztertu nahi dugun hipotesia beraz, zera da: WordNet-eko ezagutza paradigmatikoa baliagarria dela adiera-desanbiguazioan eta Dentsitate Kontzeptuala beste erlazio-izaera paradigmatikoen formalizazioak baino hobeto baliatzen dela horretaz.

IV.C.1. Algoritmoa

Adiera-desanbiguatzailearen sarrera SemCor-eko bertako testuak direnez, lehenbizi testu horien garbiketa egin behar da: lematizatu, izenak ez direnak bota eta WordNet-en ez dauden izenak baztertu. Bai lema eta bai kategoria jakiteko SemCor-en bertan dagoen informazioa erabiltzen da. 11. irudian azaltzen da esaldi baten adibide bat. Esaldi horretatik WordNet-eko izenak ez direnak ezabatu eta lemak bakarrik utziz gero, irudiaren azpiko bost izenak gelditzen dira, algoritmoak desanbiguatu beharko dituenak hain zuzen ere.

[52] Berdina uste dugu, aurreko kapituluan aipatu bezala, corpus eta hiztegietatik erauzi daitekeen informazioari buruz.

```
The jury(2) praised the administration(3) and operation(8) of the Atlanta
Police_Department(1), the Fulton_Tax_Commissioner_'s_Office, the Bellwood and
Alpharetta prison_farms(1), Grady_Hospital and the Fulton_Health_Department.

<s>
<wd>jury</wd><sn>[noun.group.0]</sn><tag>NN</tag>
<wd>administration</wd><sn>[noun.act.0]</sn><tag>NN</tag>
<wd>operation</wd><sn>[noun.state.0]</sn><tag>NN</tag>
<wd>Police_Department</wd><sn>[noun.group.0]</sn><tag>NN</tag>
<wd>prison_farms</wd><mwd>prison_farm</mwd><msn>[noun.artifact.0]</msn>↵
      <tag>NN</tag>
</s>
```

$\Downarrow$

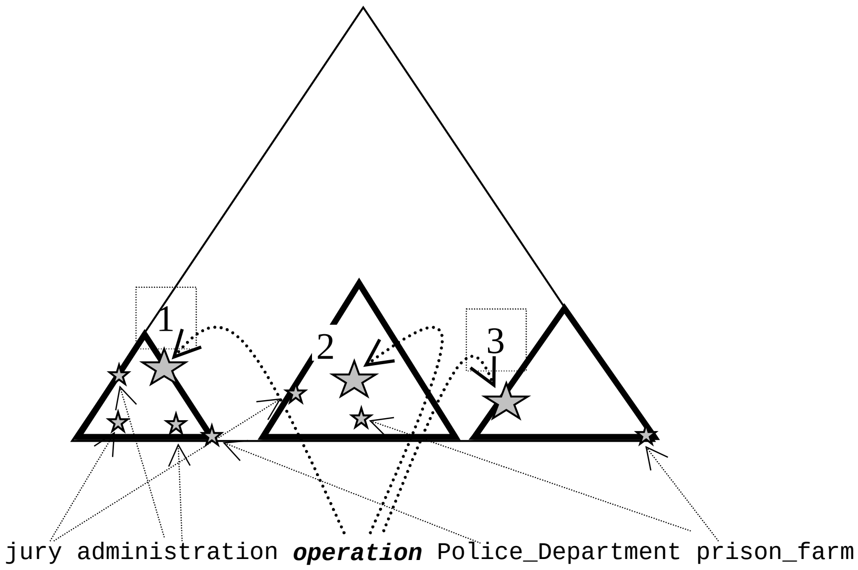
```
jury administration operation Police_Department prison_farm
```

11. irudia: SemCor formatua eta algoritmoaren sarrera

Hitzak desanbiguatzean III. kapituluan definitutako erlazio-izaera erabiliko dugu, Dentsitate Kontzeptuala. Demagun 11. irudiko *operation* hitza desanbiguatu nahi dugula, bere testuinguruari gehien lotzen zaion adiera aukeratuaz. Horretarako *operation*-en adiera bakoitzeko, bere testuinguruan dauden izenentzat (hobe esanda, izen horien adierentzat, arrastoentzat[53]) Dentsitate Kontzeptuala kalkulatu, eta Dentsitate handiena lortzen duen adiera aukeratuko dugu. Hobeto esanda, azpizuhaitz bakoitzak duen Dentsitatea kalkulatzen da, eta desanbiguatu behar den hitzaren adiera bat duen Dentsitate handieneko azpizuhaitza aukeratuko da.

Adibidez, demagun 11. irudiko 5 izenen adierak 12. irudiko izartxoak direla. *Operation* hitzak 3 adiera ditu, 1, 2 eta 3. Adiera horiek WordNet-en hierarkian (hiruki zabalena) kokatu eta hierarkiako azpizuhaitz guztien Dentsitatea kalkulatu ondoren, *operation*-en adiera bat duten zuhaitzen artean Dentsitate handienekoak 12. irudian lodiz azaltzen diren hirukiak direla ateratzen zaigu. Itxuraz Dentsitate handienekoa ezkerreko azpizuhaitzak duenez *operation*-en lehenbiziko adiera aukeratuko luke algoritmoak. Benetako algoritmoa, orain ikusiko dugun bezala, zertxobait konplexuagoa da.

[53] Arrasto deitzen genien beren arteko erlazio-izaera neurtu nahi genuen adierei (ikus III.B.2 atala).



12. irudia: izen baten desanbiguazioa Dentsitate Kontzeptuala erabiliaz. Adieren kopuru eta kokapena asmatutakoak dira.

Programak egiten duen lehenbiziko gauza leiho bat definitzea da: leiho horren erdian dagoen izena da desanbiguatu beharrekoa, eta gainontzeko izenak testuingurua. Behin leiho-zabalera jakin bat emanda, programak leihoa ezkerretik eskuinera mugituko du, izen bat mugimendu bakoitzean. Erdiko izen hori desanbiguatzeko algoritmoaren pseudokodea 13. irudian azaltzen da.

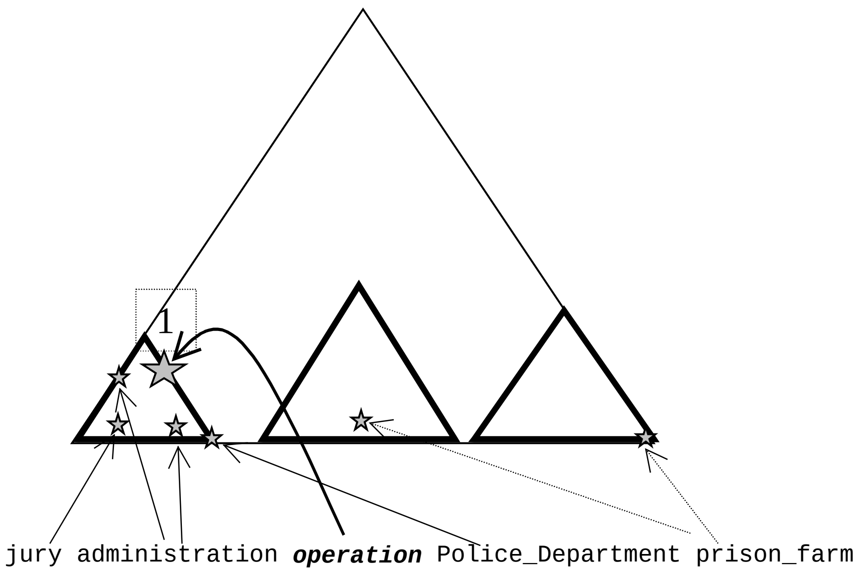
```
(1)   hierarkia := proiekzioa (hierarkia_osoa, izena, testuingurua)
      bigizta
(2)      hierarkia := konputatu_DK(hierarkia)
(3)      azpizuhaitza := DK_handieneko_azpizuhaitza(hierarkia)
         baldin azpizuhaitza = hutsa orduan atera bigiztatik
(4)      hierarkia := markatu_desanbiguatuak(hierarkia,azpizuhaitza)
      ambigizta
(5)   adiera := aukeratu_adiera(izena, hierarkia)
```

13. irudia: izen bat desanbiguatzeko algoritmoa.

Lehenbiziko pausuan, testuinguruko izenen eta desanbiguatu nahi den izenaren adiera eta hiperonimoekin hierarkia bat eraikitzen da (WordNet-en azpimultzo bat). Ondoren, 2. pausuan, Dentsitate Kontzeptuala konputatzen da WordNet-eko azpizuhaitz bakoitzarentzat, bakoitzak duen arrasto kopuruaren arabera (20. ekuazioko a_Z, ikus III. kapituluko 19. ekuazioa ere). Horretarako nahikoa da eraiki berri den hierarkiako azpizuhaitzen Dentsitatea kalkulatzea, WordNet-eko gainontzeko azpizuhaitzek, arrastorik ez dutenez, Dentsitatea 0 izango dute eta. Dentsitate handieneko zuhaitza 3. pausuan aukeratzen da. 4.ean azpizuhaitz horretan zeuden adierak landutzat hartzen dira, Dentsitate Kontzeptual handiena beraien artekoa da eta. Adiera horien hitzak landuta daudenez, hitz horien beste adierak baztertu eta hierarkiatik ezabatu egiten dira.

$$\text{dentsitate}(Z, A) = \text{dentsitate}(Z, a_Z) \quad \text{non } a_Z = |Z \cap A| \tag{20}$$

12. irudiko azpizuhaitzetan dentsoena ezkerrekoa balitz, orduan azpizuhaitz horretako adierak hautatu dira eta dagozkien hitzak landutzat hartzen dira, beraien gainontzeko adierak baztertuaz (ikus 14. irudia): adibideko *jury*, *administration*, *police_department* eta *operation* bera hain zuzen ere (gezi sendoez markatuta daudenak). Horietatik hiru guztiz desanbiguatuta daude, adiera bakarra baitute azpizuhaitz dentsoenean, baina *operation*-ek bi adiera ditu. Landu gabe dagoen hitz bakarra *prison_farm* da.



14. irudia: izen baten desanbiguazioa Dentsitate Kontzeptuala erabiliaz. Adieren kopuru eta kokapena asmatutakoak dira.

Adierak azpizuhaitz horretan ez dituztela eta, hitz batzuk oraindik landu gabe egon daitezke, eta beraz hierarkiako Dentsitate Kontzeptual handieneko hurrengo azpizuhaitza aukeratzeko beste bigizta bat behar da. Hitz guztiak landu direnean (edo ezin denean ezer gehiago landu, adibidez 14. irudiko *prison_farm*-en kasuan) orduan bigiztatik atera eta 5. pausuan desanbiguatu nahi genuen hitzari dagokion emaitza bueltatuko da. Hiru aukera daude emaitzari dagokionez:

1. Adiera bat aukeratzea, azpizuhaitzean adiera bakarra zegoen eta.
2. Adiera anitz aukeratzea, azpizuhaitzean hitzaren adiera bat baino gehiago zegoen eta.
3. Adierarik ez aukeratzea, adiera guztiak isolatuta zeudelako.

14. irudiko hitzentzat honako litzateke emaitza: *jury*, *operation* eta *police_department* guztiz desanbiguatu dira, adiera bakarra baitute. Landuta baino desanbiguatu gabe gelditzen da *administration*, bi adieraz, eta landu gabe *prison_farms*, bi adierarekin ere.

Ikusten den bezala leihoaren erdiko izena desanbiguatzerakoan leihoko gainontzeko izenak ere desanbiguatzen dira. Izan ere algoritmo hau testua zatika desanbiguatzeko diseinatua dago. Tamalez SemCor-en ez dago paragrafo edo antzeko zatiketen adierazlerik, eta horregatik hautatu genuen hitzak banan-bana desanbiguatzea esperimentu honetan.

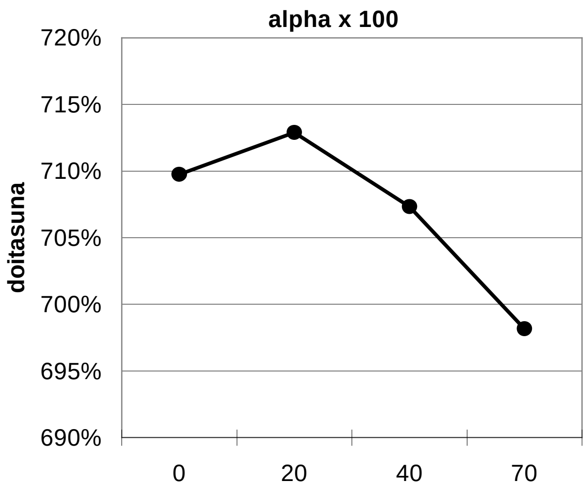
IV.C.2. Dentsitate Kontzeptualaren aldaeren ebaluazioa

Esperimentuen emaitzak lau fitxategietan lortutakoaren batezbestekoa kalkulatuz ematen dira. Desanbiguazioa ez denean erabatekoa, hau da, adiera bat baino gehiago aukeratu direnean, desanbiguatu ez balu bezala hartuko dugu. Bi neurri erabiliko ditugu ebaluazioan: doitasuna (desanbiguatutako izenetatik ondo daudenen ehunekoa) eta estaldura (izen guztietatik zenbat desanbiguatu izan diren, ehunekotan), beti ere hitz polisemikoentzat kalkulatuta. Taula gehienetan emaitzak leihoaren zabaleraren arabera eman ohi dira, zabalera izenen arabera kalkulatuta egonik.

IV.C.2.a) Parametroa: α

Leihoaren tamaina handitzen denean, azpizuhaitz jakin baten azpian dagoen arrasto kopurua azpizuhaitzaren altuera baino dezente handiagoa izan daiteke. Horrelakotan III. kapituluko 18. formulako zatikizuna gehiegi handitu daiteke. Efektu hori leuntzeko parametro bat gehitu genion formulari, enpirikoki aztertu eta balioa bilatu dioguna (ikus III. kapituluko 19. ekuazioa).

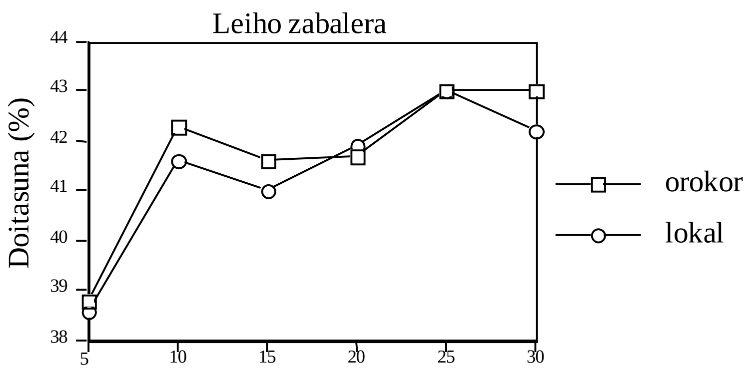
Parametroaren balio onena bilatzeko esperimentu sorta zabala egin genuen, hainbat leiho-zabalera eta testuren gainean, α-ren 0tik 1erako aukerak probatuz. 15. irudian egindako 20 esperimentutan batutako doitasunak azaltzen dira. Bai grafiko honetan, eta baita egindako beste esperimentu batzuetan ere, garbi ikusten da desanbiguazio emaitza hoberenak α 0,2 baliotik hurbil dagoenean lortzen direla, nahiz eta aldea txikia izan: 15. irudian, adibidez 0,2 eta 0,4 artean dagoen aldea 20 esperimentuetan %5 ingurukoa da, baina esperimentu bakoitzerako batez-beste %0,25koa da bakarrik. Beraz, aurrerantzean azaltzen diren esperimentu guztietan α-k 0,2 balioa izango du.



15. irudia: α parametroaren balioen araberako doitasuna.

IV.C.2.b) Nola kalkulatu μ_Z

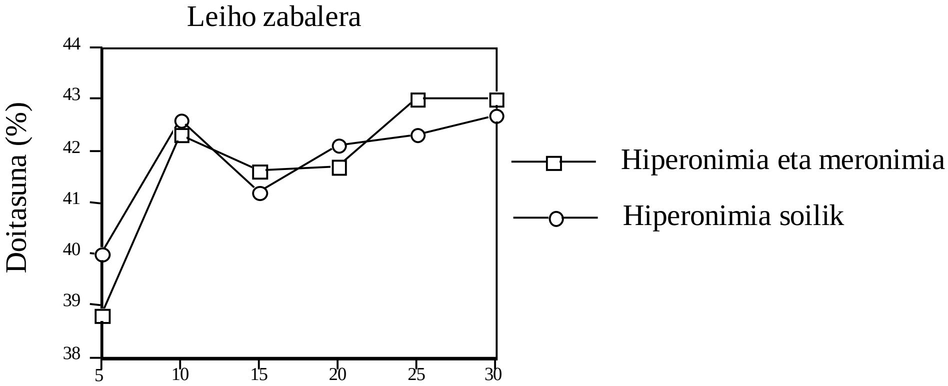
Aurreko kapituluan azaldu bezala umeen batezbestekoa azpizuhaitz bakoitzerako erabili ordez (μ_Z lokala), WordNet ontologia guztirako batezbestekoa (μ_{WN} orokorra) erabili daiteke. Honen eragina zein den aztertzeko hainbat esperimentu egin genituen leiho zabalera ezberdinak kontuan hartuaz (ikusi 16. irudia) eta μ_Z lokala erabiliaz doitasuna ozta-ozta hobetzen dela ondorioztatu genuen. Kontuan hartuz μ_{WN} orokorra erabiltzea eraginkorragoa dela, berau erabili genuen gainontzeko esperimentuetan.



16. irudia: μ_Z lokala edo μ_{WN} orokorra

IV.C.2.c) WordNet-eko beste erlazioak: meronimia

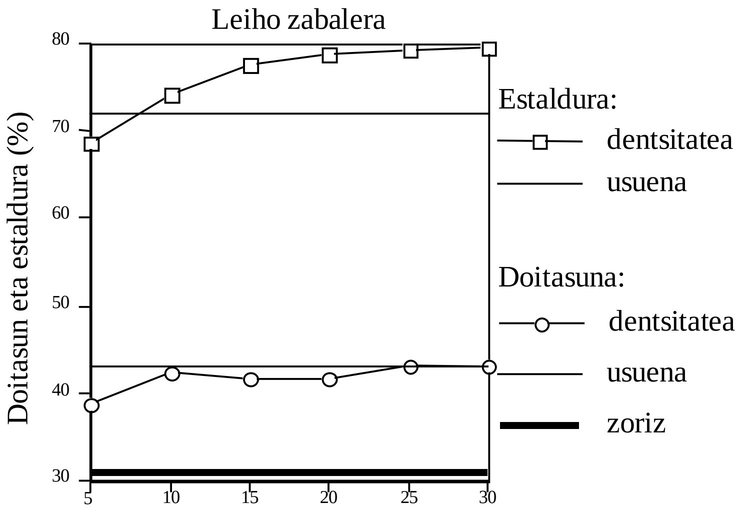
Enpirikoki aztertu dugu Dentsitate Kontzeptualak meronimia erlazioak ere erabiltzean desanbiguatzailearen doitasunean eraginik daukan edo ez. Emaitzen arabera (17. irudia), doitasuna antzekoa dela ondorioztatu daiteke, baina estaldura %3 altxatzen da, eta beraz meronimia erlazioak erabiltzea erabaki genuen.



17. irudia: meronimia erabiltzearen eragina

IV.C.3. Ebaluazioa

Orain arte faktore jakin batzuk aztertu ditugu, onuragarriak diren edo ez erabakitzeko. Orain emaitza orokorrak aztertuko ditugu. 18. irudian azaltzen den bezala, testuinguruaren leihoa zabaltzen den heinean estaldura handitu egiten da. %80 inguruan egonkortzen da, 20 izen baino leiho zabalagoetarako hobekuntza gutxi jasoz. Doitasuna, bestalde, %43raino igotzen da leihoa zabaldu ahala.



18. irudia: doitasuna eta estaldura

Irudian bi *baseline* azaltzen dira: zorizkoa eta SemCor-eko izenen adiera usuenak aukeratzekoa. Lehenbiziko kasuan doitasuna (%30 inguru) analitikoki kalkulatu genuen, testuetako hitz polisemikoen adiera kopuruak erabiliz. Ondoren enpirikoki baieztatu genuen, 10 aldiz egikarituaz adierak ausaz aukeratzen zuen programa. Estaldura, noski, %100eko litzateke. Adiera usuenak aukeratzeko beharrezkoa da eskuz desanbiguatutako materiala edukitzea. Adieren maiztasunak kontatzeko SemCor bera erabili genuen, aukeratutako lau testuak kontuan hartu barik. Doitasuna Dentsitate Kontzeptualaren berdina da, baina estaldura %8 apalagoa.

Leiho hoberenarentzako datuak 13. taulan azaltzen dira. Oraingoz adiera mailako doitasunari buruz hitz egin dugu, aurrerago ikusiko dugu fitxategi mailako doitasunaren esanahia. Irudietan azaltzen diren datuak izen polisemikoentzat dira bakarrik, baina adiera bakarreko izenak ere kontuan hartzen baditugu doitasuna %64,5era eta estaldura %86,2ra iristen dira.

leihoa=30		Estaldura	Doitasuna
polisemikoak	adiera	%79,6	%43,0
	fitxategi		%53,9
guztira	adiera	%86,2	%64,5
	fitxategi		%71,2

13. taula: leiho hoberenarentzako datuak

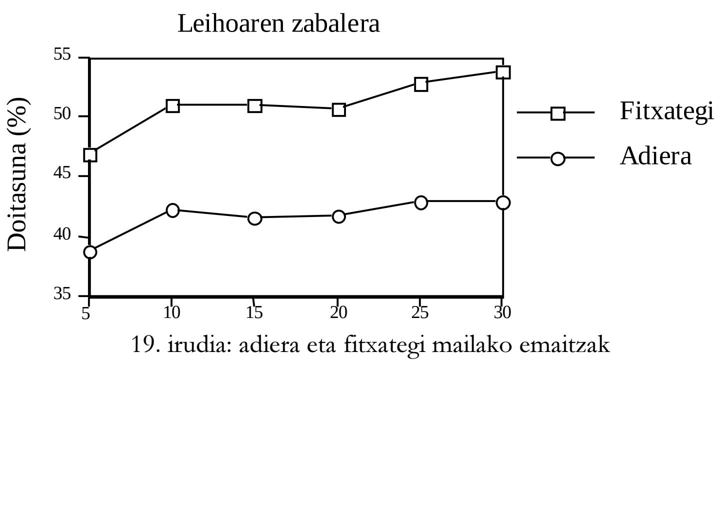
Ebaluazio orokorraz gain, emaitzak beste ikuspuntu batzuetatik ere aurkeztu ditugu.

IV.C.3.a) Desanbiguazio maila: adiera edo fitxategia

WordNet-ek adierak lexikografoen fitxategietan multzokatzen ditu. Izenen kasuan fitxategi horiek domeinuaren inguruko irizpidez egituratu dira, eta 25 daude. Gure algoritmoak izenari adiera egokia bilatzeaz gain fitxategia ere esleitzen dio. Gure ustez granularitate maila biak dira interesgarriak, WordNet adiera bereizketak xeheegiak direla esan izan baita, eta fitxategi mailako bereizketa zabalagoa da.

Homografo edo domeinu mailan beste algoritmoek eman izan dituzten bereizketak baino xeheagoa da hala ere, adibide batez ikusiko dugun bezala. Yarowsky-k (1992) *bass* izenarentzat bi adiera bereizten zituen: *MUSIC* bezala etiketatzen zuen bata, eta *ANIMAL* bezala bestea. WordNet-en aldiz 9 adiera bereizten dira. Musikari buruzko 6 adierak 4 fitxategitan daude banatuta: *ARTIFACT*, *ATTRIBUTE*, *COMMUNICATION* eta *PERSON*. Animaliei buruzko 3 adierak aldiz bi fitxategitan azaltzen dira: *ANIMAL* eta *FOOD*. Yarowsky-k 2 adiera bereizten zituen lekuan, WordNet-en fitxategi mailan 6 leudeke, eta adiera mailan 9.

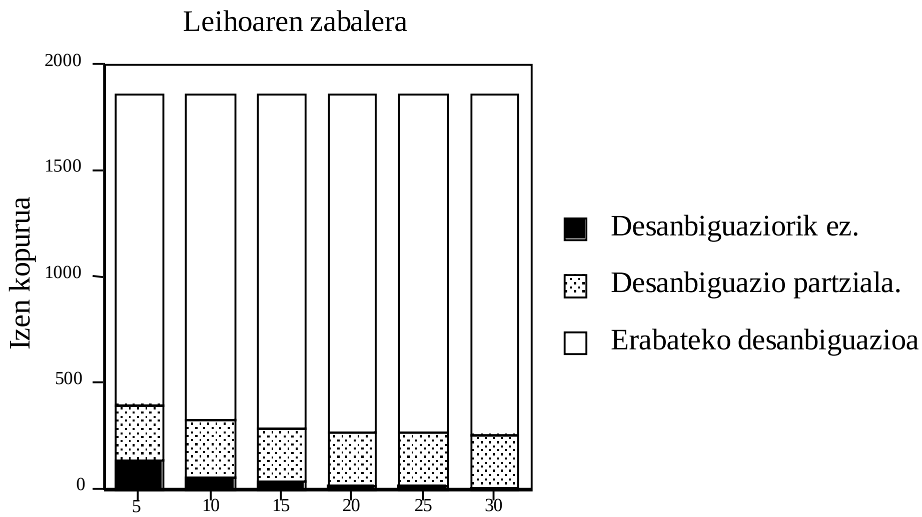
Fitxategi eta adiera mailako emaitzak konparatzeko jo 13. taulara eta 19. irudira.



19. irudia: adiera eta fitxategi mailako emaitzak

IV.C.3.b) Desanbiguazio partziala

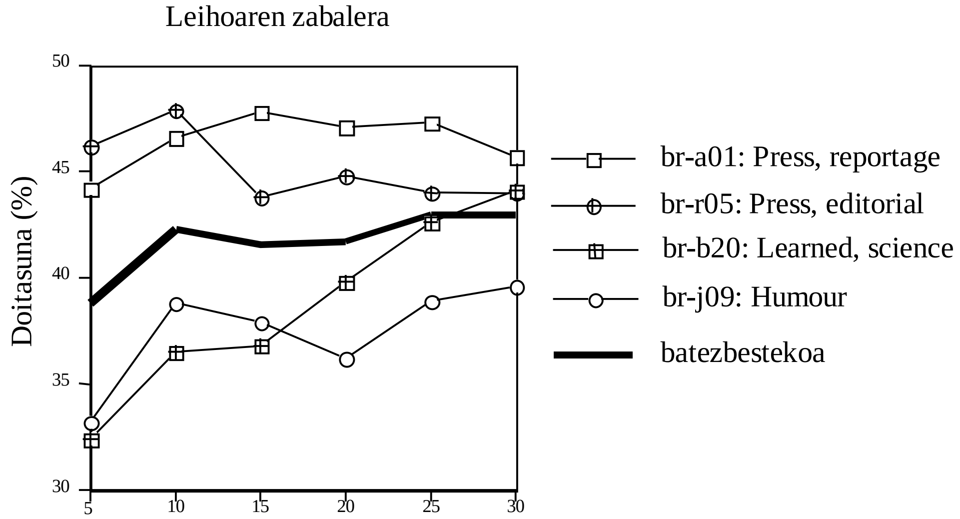
Aipatu izan dugun bezala gure algoritmoak adiera bakarra aukeratzeaz gain badauzka beste bi aukera: adiera multzo bat aukeratzea edo bat ere ez aukeratzea. Adiera multzo bat aukeratu izan duenean, orain arteko emaitza guztietan desanbiguatu izan ez balu bezala hartu dugu. 20. irudian ikusten den bezala, algoritmoaren estaldura %80koa dela esan dugunean, ez ditugu hartu kontuan partzialki desanbiguatutakoak. Leiho zabalenaren kasuan partzialki desanbiguatutakoak kontuan hartu izanez gero, %100eko estaldura izango genuke.



20. irudia: desanbiguazio partziala

IV.C.3.c) Testuinguruaren zabaleraren eragina

Lehenago azaldutako datuetan desanbiguatu izan diren lau fitxategietarako lortutako emaitzen batezbestekoa erabili da. Horrela, testuingurua zabaldu ahala doitasunaren emaitzak hobetzen direla ikusi dugu. Hala ere, fitxategi horien egitura eta topikoa hain ezberdinak izanda, ez genuen espero ezaugarri hori guztientzat beteko zenik. Eta hala gertatzen da, 21. irudian ikusten den bezala.



21. irudia: testuinguruaren zabaleraren eragina testu fitxategietan

Testu-fitxategi bakoitzaren portaera ezberdinaren arrazoia, testuen domeinu ezberdinaz gain, SemCor-en akats batean ere egon daiteke. Izan ere fitxategiak esaldi segida bezala daude egituratuak, titulu, atal, paragrafo edo testuaren iturriaren aldaketa adierazi barik. Izenak diskurtso berean gertatzen diren jakin gabe pilatzen du testuingurua algoritmoak. Horrek argi lezake elkarrizketa oso motzez osatutako br-r05 fitxategian doitasun hoberena 10 izeneko zabalerarekin lortzea, edo prentsako editorialak dauzkan br-b20 fitxategian testuinguru txikiekin emaitza askoz okerragoak lortzea.

IV.D. Konparazioa beste metodoekin

Dentsitate Kontzeptualaren emaitzak beste lanekin konparatzea zaila da. Emaitzan izugarri eragiten duten faktoreak ezberdinak izaten dira lan batetik bestera: adiera bereizketaren iturri eta granularitatea, zenbat hitzekin probatu izan den (hitz multzotxoa edo testu errealetako hitz guztiak), zein kategoriekin probatu den, ontzat emateko irizpideak (emaitza partzialak, adiera bat baino gehiago ontzat emateko aukera), ebaluaziorako neurri ezberdinak, etab. Bestalde desanbiguatzaile batzuk *standalone* sistema (desanbiguatzeko beharrezko guztia dakiena) bezala aurkezten diren bitartean, beste algoritmo batzuk, gurea barne, ezagutza iturri osagarriekin integratu beharko liratekeen azpisistema bezala planteatu izan dira.

Faktore horiek kontuan eduki gabe, ezin da emaitzen arteko konparazio hutsa egin. Gure sistemak zailtasun handieneko ebaluazioari egiten dio aurre: adiera bereizketa xeheak, testu errealetako izen guztiak, emaitza partzialak baztertu eta adiera bakarra ontzat eman. Horregatik gure sistemaren doitasuna (%43) ezin da, adibidez, Yarowsky-ren 1995.ekoaren parean jarri (%97).

Sistemen arteko konparazioa, beraz, ez dugu horrela egingo. Konparaziorako hautatu dugun bidea zera izan da, WordNet-eko ezagutza erabili izan duten edo erabiltzera egokitu daitezkeen sistemak gure testuen gainean lanean jarri eta emaitzak konparatzea. Horretaz gain WordNet erabili izan duten bestelako lan batzuk ere laburki aipatuko ditugu.

Gure lanarengandik hurbilen dagoena Sussna-rena (1993) da (ikusi III.A.1 atala eta kapitulu honetako IV.A.2 atala). III. kapituluko III.D atalean ere aipatu ditugu Dentsitate Kontzeptualak Distantzia Kontzeptualarekin alderatuta dauzkan abantailak. Sussna-k, gure antzera, domeinu publikoko corpus bateko testu batzuetako izenak desanbiguatu zituen. Guk ez bezala, adiera bat baino gehiago onartzen zituen, eta adiera egokia topatzen ez zuenean ebaluaziotik baztertu egiten zuen. Binakako Distantzia Kontzeptuala erabiltzeak dakarren leherketa konbinatorioa saihesteko testuinguruaren leihoa 10 izenetara mugatu beharra zeukan[54], edo testuingurua zabaldu nahi izanez gero, behin izen bat desanbiguatu ondoren hurrengo izenen testuinguruak aukeratutako adiera hori erabili behar zuten testuinguruan (adierak geldiaraztea deitu zion honi, *freezing*). Hori dela eta, adiera bat gaizki aukeratuz gero, hurrengo izenetarako erabakia okertu zitekeen. Adiera bakarra aukeratzera ere derrigortzen du honek, eta horretarako, adiera bat baino gehiago egokiak direnean, bat ausaz aukeratu beharra dauka.

Sussna-ren arabera emaitza hoberenak ematen zituen algoritmoa inplementatu dugu, garrantzi gutxiko faktoreak alde batera utzita[55]. Emaitzak konparatu ahal izateko Dentsitate Kontzeptualak adiera bat baino gehiago hautatzen duenean ausaz aukeratzera behartu dugu. 14. taulan ikus daitekeen bezala, Dentsitateak doitasun hobeagoa lortzen du. Sussna-k bere lanean aurkeztutako emaitzetan izen monosemikoak kontuan hartuz gero %63,4ko emaitzak azaltzen ditu, hemengoak baina %10 hobeagoak. Izen guztientzat erabaki beharra eta adiera on bakarra existitzeak eragina eduki dute, ziur aski, bere artikulu eta gure esperimentuaren arteko aldean.

		Estaldura	Doitasuna[56]
Sussna, 1993	Adiera	%100	%52,3
	Fitxategia		%64,5
Dentsitatea (leihoa=30)	Adiera	%100	%60,1
	Fitxategia		%70,1

14. taula: Sussna (1993) eta Dentsitatea

[54] Bere algoritmoa br-r05-eko lehenbiziko 10 izenekin erabiltzean, 200.000 adiera pareren arteko distantzia kalkulatu izan behar genuen.

[55] Hasierako 10 hitzen adierak batera aukeratu, eta hortik aurrera adierak geldiarazten ditu 41 izenetako leihoak erabiliaz. Meronimia-erlazioak ere erabili dira,eta erlazio guztiak pisu bera eduki dute.

[56] Taula honetan doitasuna izen guztientzat ematen da, hau da, adiera bakarrekoak ere kontuan hartuta.

Aipatu beharra dago gureari lotutako lan bat, (Resnik, 1997) (ikus III.A.4 atala, eta kapitulu honetako IV.A.5 atala). Erlazio-izaera erlazionatutako izen multzoen gainean probatu zuen, printzipioz errazagoa dirudien lana, WordNet-eko adiera xeheak erabiliaz. Berak gutxi gora bera %40ko doitasuna aipatzen du, gure %43 baino %3 apalagoa.

Eskuzko lanik behar ez duen lan arrakastatsu bat Yarowsky-k (1992) egindakoa da. Ontologia bat (*Roget's thesaurus*) eta corpus bat (*Grollier's Enciclopedia*) konbinatu zituen, corpus bereko 12 izenei ontologiako klase marka jartzeko asmoarekin. Bere algoritmoa (ikusi III.A.4 atala ere) inplementatzeko ontologiako klase bezala WordNet-eko lexikografoen fitxategiak erabili ditugu. Bere algoritmoaren emaitzak eta fitxategi mailan Dentsitateak lortutakoak 15. taulan azaltzen dira. Dentsitatearen doitasuna %7 garaiagoa da. Nahiz eta zorizko hautaketaren bitartez Dentsitatearen estaldura %100era igo (ikusi 14. taula) Dentsitatearen doitasunak hobeagoa izaten jarraitzen du (%70,2).

	Estaldura	Doitasuna
Yarowsky, 1992	%100,0	%64,0
Dentsitatea	%86,2	%71,2

15. taula: Yarowsky (1992) eta Dentsitatea

WordNet-en oinarritutako adiera bereizketa darabilten bi lan (Leacock et al., 1998) eta (Towell & Voorhees, 1998) dira, baina adiera bereizketa ez da hain xehea[57]. Biak daude batez ere corpusetan oinarrituta; bigarrenak bakarrik darabil WordNet-eko ezagutza, nahiz eta sinonimia erlaziora bakarrik mugatu.

IV.E. Ekarpena

Kapitulu honetan WordNet-eko ezagutza paradigmatikoa darabilen Dentsitate Kontzeptualean oinarritutako desanbiguatzailea eraiki eta probatu dugu. Emaitzen arabera Dentsitate Kontzeptuala HADrako erabilgarria dela frogatu dugu, eta WordNet-eko ezagutzaz erlazio-izaera paradigmatikoen beste formalizazioak baino hobeto baliatzen dela erakutsi ere bai. Hurbilpen honek adieraren definizio sendo bati heltzen dio, eta corpusetan oinarritutako tekniken arazorik ez du, hala nola eskuzko desanbiguazioaren beharrik edo datu urrien arazorik.

Gure sistemaren onurak:

- Ontologia bateko adieratara lotzen ditu testu errealetako izenak.

[57] Beraien lanean erabilitako izen bakarrarentzat (*line*) 6 adiera bereizten dituzte. WordNet-ek bereizten dituen adierak 27 dira.

- Oinarri teoriko sendoak dituen erlazio-izaera erabiltzen du.
- Emaitza onak, nahiz eta testu zailetan probatu dugun.
- Edozein domeinutan erabil daiteke inongo egokitzapen beharrik gabe.
- Konplexutasun aldetik erakargarria.
- Ez du eskuzko desanbiguazioaren beharrik.
- Ez du datu urrien arazorik.

HADaren literaturan azaltzen diren esperimentuekin alderatzean gure esperimentuak arazoaren alde zailenari egin dio aurre: adiera bereizketa xeheak, testu errealetako izen guztiak, emaitza partzialak baztertu eta adiera bakarra ontzat eman. Enpirikoki frogatu dugu Sussna (1993) eta Yarowsky (1992) baina emaitza hobeagoak lortzen dituela testu sail berdinean, ausaz aukeratu izan diren lau testu zabal erabiliaz (guztira 10.000 hitz). Testuak ez ziren inolaz ere errazak desanbiguatzeko. Adibidez, horietako bat humorezko elkarrizketa motzez osatua zegoen. Hala ere, WordNet-eko adiera finetarako desanbiguatzean %64ko doitasuna lortzen dugu, eta fitxategi-mailan desanbiguatzen badugu %71koa. Estaldura oso zabala da, testuetako izenen %86 desanbiguatzen dugu eta.

IV.F. Etorkizunerako lana

Egindako esperimentuetan baziren hobetu zitezkeen alor batzuk.

- Diskurtso-egituraren araberako testu zatiak batera desanbiguatu. SemCor corpusak, tamalez, ez du paragrafo markarik, eta ezinezkoa izan da testuak diskurtsoaren egituraren arabera zatitzea. Horrela egin izanez gero hitzak bakarka desanbiguatu ordez testu zati oso bat batera desanbiguatu zitekeen, eraginkortasun hobeagoa lortuaz. Gainera doitasuna ere hobetuko litzateke, zerikusirik ez daukaten testu zatiak alde batera utziko ziren eta.
- Dentsitatearen neurri eta adiera-aukeraketaren artean koerlaziorik ote dagoen ikertzea interesgarria izango litzateke. Koerlazio bat balego Dentsitatearen balio batetik behera daudenak desanbiguatu gabe utzi eta doitasuna hobetuko litzateke (estaldura gutxitzearen truke).

Desanbiguazioaren emaitzei dagokionean, emaitza hobeagoak lortzeko informazio iturri berriak gehitzea ezinbestekoa da. Gure ustez Dentsitate Kontzeptualak WordNet-ek duen ezagumendu paradigmatikoa ezin hobeto ustiatzen du, baina horrekin ez da nahikoa. Kapitulu honetako IV.A.1

atalean ikusi dugun bezala bestelako ezagutza iturriak ere erabili behar dira. Bi sailetan bereiziko genuke ezagumendu hori:

- Dentsitate Kontzeptualean integratu beharreko ezagumendua, WordNet aberastuaz lortuko zena (ikus III. kapituluko etorkizunerako lanari buruzko atala).
- Desanbiguazioan erabilgarriak diren bestelako ezagutza. Honen adibideak dira, adibidez, adieren maiztasunak, bai orokorrean edo desanbiguatzen ari garen testuan, ea adiera bat kolokazio modura azaltzen den, adiera bakoitzaren inguruan dagoen egitura sintaktikoari buruzko informazioa (pista sintaktikoak, ikus Leacock et al. 1998), eta abar.

Horrela adiera-desanbiguaziorako sistema osoago bat eraikiko genuke, Dentsitate Kontzeptualaren bidez informazio lexikal-semantikoa kodetzen duena eta hau beste ezagutzarekin konbinatzeko gai dena.

Tesi hau idazten ari garen bitartean, SENSEVAL txapelketa[58] gertatzen ari da. Mundu mailan adiera desanbiguatzen duten sistema hoberenek parte hartzen dute bertan. Yarowsky-ren (1995) lana, Dentsitate Kontzeptuala eta hiztegietan oinarritutako bestelako erlazio-izaeraren neurriak (VI. kapituluan ere azalduko zaizkigunak) integratzen saiatzen ari gara txapelketa horretarako.

Aurreko kapituluan aipatu dugun bezala, adiera-desanbiguaziorako algoritmoaren inplementazio azkarrago bat lantzen ari gara, UNED-eko Elektrizitate eta Elektronika saileko ikerkuntza taldearekin batera, ITEM[59] proiektuaren barruan. Bertsio hau ingeniaritza linguistikorako GATE[60] ingurunearen barruan (Cunningham et al. 1997) integratuta egongo da laster.

[58] http://www.itri.bton.ac.uk/events/senseval/cfp2.html

[59] http://sensei.ieec.uned.es/item/

[60] http://www.dcs.shef.ac.uk/research/groups/nlp/gate/

V. Kapitulua

TESTU-ZUZENKETA AUTOMATIKOA

Kapitulu honetan Dentsitate Kontzeptuala beste alor baten aplikatzen saiatuko gara, testu-zuzenketa automatikoan. Gure ikerkuntza taldeak testu-zuzenketan egindako ikerkuntzan tradizioa badu, eta zuzenketa proposamenak automatikoki aukeratzea zein puntutaraino posible den edo ez aztertu nahi izan dugu. Horretarako ez dugu Dentsitate Kontzeptuala bakarrik erabiliko, ezagutza sintaktikoa ere guztiz beharrezkoa baita. Lehenbizi, V.A. atalean, testu-zuzenketa alorraren sarrera txiki bat eta aurrekarien azterketa egin ditugu. V.B. atalean esperimentua bera egin baino lehenagoko aurre-azterketaren berri eman dugu. Ondorengo atalean esperimentuan erabilitako teknika guztiak labur azaldu, eta, V.D. atalean, esperimentuaren diseinua, emaitzak eta ebaluazioa aipatzen dira. Azkenik kapitulu honetako ekarpenen laburpena eta etorkizunerako lanak aurkezten dira.

V.A. Sarrera eta aurrekariak

Testuetako idazketa-erroreen ordenadore bidezko zuzenketa oraindik ikertzen ari den alorra da. Arazo honen ebazpen idealean, testuan egindako errore guztiak programa batek automatikoki zuzenduko dizkiola espero du erabiltzaileak. Gaur egun ordea, testu-prozesadoreetan (Word, 1997; Ispell, 1993; Aduriz et al. 1997) aurkitzen duguna zuzenketarako laguntza besterik ez da izaten:

- Sakatze edo ortografia erroreak detektatuz. Adibidez:

```
Lehio* bat apurtu dut.
Ukenduaren uzainak* erlea aldendu zuen.
Araso* hau konpontzeko eskatu dut.
```

- Errore horren ebazpen posibleen zerrenda bat emanaz. Adibidez:

```
lehio*: lehia, lesio, leiho
uzaina*: zaina, usaina, uhaina
araso*: eraso, arazo, arasa, arbaso
```

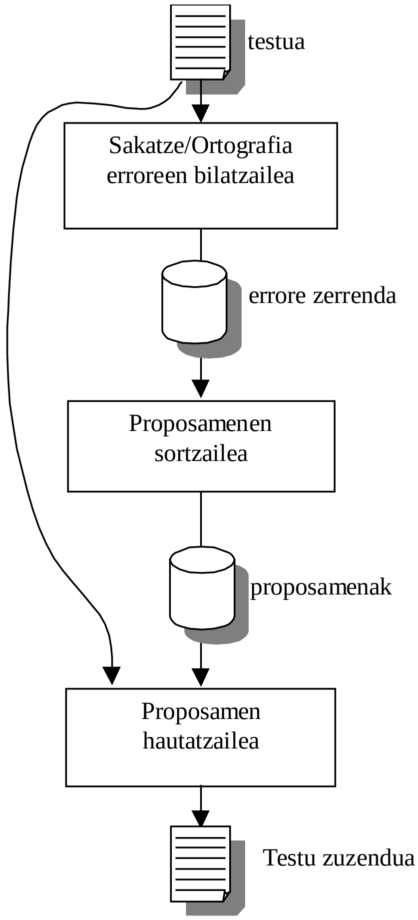
Sistema hauek muga garbi batzuk eduki ohi dituzte (Kukich, 1992):

- ortografia erroreek hitz posible bat sortzen badute, ezin da detektatu. Adibidez, `usaina` idatzi nahi eta sakatze errore baten ondorioz `uhaina` idazten dugunean. Errore mota honi *benetako hitza* errore deituko diogu (*real-word error*), eta kontrakoari, hau da, errorearen erruz idatzitako hitzak ez denean existitzen, *ez-hitza* errore deituko diogu (*non-word error*).

- Proposamen bakarra ezin eman izatea. Hau da zuzenketa guztiz automatikorako (giza-zuzentzailearen parte hartze gabekoa) oztopo garrantzitsuena.

- Errore gramatikalak topatzeko zailtasunak. Adibidez konmuztadura erroreak: `nik izan naiz`. Nahiz eta gramatikaren alor honetan laguntzen saiatu, gaur egungo testu-prozesadoreen laguntza mugatua da oso, alarma faltsu gehiegi eta ezer gutxi zuzentzen dutelako. Testu-prozesadoreak batez ere ez-hitza erroreen zuzenketara mugatzen dira.

Kapitulu honetan azalduko den hobekuntza **proposamen bakarraren** ildotik doa, hau da, sakatze edo ortografia erroreak detektatu ondoren proposatzen diren zuzenketetatik bakarra aukeratzea. 22. irudian zuzentzaile baten eskema ikus daiteke. Guri interesatzen zaigun modulua proposamen-hautatzailearena da: errorearen testuingurua aztertu eta horren arabera testuinguruari hoberen lotzen zaion proposamena aukeratzen du. Esan bezala, beste bi moduluentzat ondo garatutako teknologia badago (Word, 1997; Ispell, 1993; Aduriz et al. 1997), baina proposamen sortzaileek ez diote erreparatzen testuinguruari eta beraz proposamen egokia aukeratzeaK –zuzenketa automatikoaK– irekita dagoen arazo bat izaten jarraitzen du (Kukich, 1992).



22. irudia: proposatutako sistemaren eskema

V.A.1. Aplikazioak eta zuzenketa automatikoaren beharra.

Testuetan aurkitzen diren erroreen iturria, ordea, ez da beti giza errakuntza. Gaur egun testua jatorri ezberdinetatik eskura daiteke: eskanerrak, arkatz optikoetan oinarritutako interfazeak, ahotsaren ezagutzarako gailuak, edo aipatu den giza-erabiltzaileak teklatuetan sakatuta. Jatorri horren arabera tratamendu ezberdina jasoko du testuak: karaktere-ezagutze optikoa (*Optical Character Recognition*) delakoa, idazkeraren ezagutza, ahotsaren tratamendua edo testu-prozesadorea. Errore baten aurrean, hala ere, antzera jokatu beharko dute: errorea dela detektatu, errore horri ebazpen proposamen zerrenda bat proposatu eta ahal dela proposamen bakarra lehenetsi. Sistema horietan guztietan ezin da orokorrean errore zuzenketari buruz hitz egin, batzuentzat egokiagoa baita hitz-ezagutzeaz hitz egitea. Hala ere azken urte hauetan bi arazo mota hauentzat ebazpide amankomunak planteatzen ari direnez, badago bien elkarketa bat (Kukich, 1992). Kapitulu honetan zehar errore-zuzenketari buruz hitz egingo dugu, baina teknika gehienak beste eremuetara ere heda daitezke.

Proposamen bakarrak ahalbideratzen duen zuzenketa automatikoa egin ahal izateko, gaur egun sistema hauek bi eratara jokatzen dute:

1. Hiztegia mugatuz, proposamenen zerrenda motzagoa izan dadin (adibidez, ahotsaren tratamenduan) [61].
2. Erabiltzailearen esku utziz, azken erabakia har dezan (testu-prozesadoreak).

Badira halere zuzenketa automatikoa beharko luketen aplikazioak, adibidez testuak ahoskatzen dituzten sistemak. Hauen kasuan beharrezkoa da, nahiz eta ahoskatu behar duten testuan erroreak egon, testu osoa ahoskatzea. Horretarako inoren laguntza gabe proposamen zuzena bilatu behar da, hiztegia mugatu gabe. Testuekin lan egiten duten edo gizakiarekin elkarrekintza duten sistemen sendotasuna eta komunikatzeko gaitasuna ere nabarmenki hobetuko litzateke. Zuzenketa automatikoak aurrerabide galanta suposatuko luke testu eta programen edizioan, ordenadorez lagundutako argitaratzean, hizkuntzen irakaskuntzan, ordenadorez lagundutako tutoreetan, datu-baseekin elkarrekintzan eta baita ahotsaren erabilera plantea daitekeen beste aplikazioetan ere (Kukich, 1992).

V.A.2. Aurrekariak

Zuzenketarako proposamenen artean zuzena aukeratzea horrela zehaztu daiteke: errorea proposamen bakoitzarekin ordezkatzean sortzen diren esaldi posibleen artean "hoberena" aukeratzea (Mays et al. 1991). Esaldi hoberena zein den erabakitzeko ezagutza-iturri ezberdinetara jo beharko dugu. Ezagutza horien inguruan egingo dugunez bibliografiaren azterketa, ikus dezagun (Mays et al. 1991) eta (Kukich, 1992) lanetan LNParen prozesamendu klasikoaren arabera eginiko iturrien banaketa zein den:

a) Erroreen iturriei buruzko ezagutza
b) Sintaxiari buruzkoa
c) Semantikari buruzkoa

V.A.2.a) Erroreen iturriei buruzko ezagutza

Lehenbizikoa bakarrik erabiltzen denean hitz isolatuen zuzenketa deritzonean (*isolated word correction*), erroreen iturburuak eta erroreak sortzen dituzten faktoreak aztertzen dira (sakatze erroreak, entzumen sistemen erroreak, eskanerren erroreak etab.). Kernighan-ek eta (Kernighan et al. 1990) horrelako sistema bat aurkezten dute. Ebaluazioa bi proposamen dauzkaten erroreentzat egiten da, %87ko doitasuna lortuz. Garai berdinean Kukich-ek (1990) proposamen kopurua edozein izanda ere lan egiten duen sistema aurkezten du, baina hiztegi murriztua behar duena (521 eta 1872 hitz

[61] Ahotsaren tratamenduan entzundako esaldiarentzat interpretazio bakarra behar izaten da. Soinutik abiatuta hitza ezagutzean aukera bat baino gehiago egoten da, eta aukera horien artean bakarra utzi ahal izateko ezagutzen diren hitzen zerrenda mugatzen da.

dituzten bi hiztegirekin egiten ditu saiakerak). Honek, noski, lan honen erabilera erreala zalantzan jarriko luke. Kukich-en emaitzak %75eko doitasunaren inguruan dabiltza. Lan berdinean, errorearen testuinguruaren berri eduki gabe gizakiak zein puntutaraino lor zezakeen hitz zuzena aukeratzea %66 eta %87 artean neurtu zuen. Bere esanetan horrek adieraziko luke ezagutza iturri hau erabiltzen duen sistema baten gehienezko doitasuna. Beranduago Ingels-ek (1997) bere tesian Kernighan-en eta (Kernighan et al. 1990) lana moldatuko du. Egindako esperimentuak bi testu sortari lotuta daude: datu-base baten galdeketa sistemako elkarrizketak eta ordenadoreen eskuliburu bat. Sistema testu horietarako trebatzen du. Lehenbiziko testuan %74ko doitasuna lortzen du, eta bigarrenean, hiztegi zabalagoa daukanean, %54ko doitasuna. Kernighan eta Ingeles-en lan hauen sintaxi-hedapenak ondoren ere aztertuko ditugu.

V.A.2.b) Sintaxia

Sintaxia erabiliko lukeen sistema batek esaldian errorea proposamen bakoitzaz ordezkatzean gelditzen den egitura sintaktikoaren egokitasuna egiaztatuko luke. Egitura onargarriei dagozkien proposamenak bakarrik aukeratuko lirateke, edo egokitasun sintaktikoaren neurri bat erabiliz gero, proposamenak egokitasun-neurri horren arabera ordenatuko lirateke. Funtsean, semantikarekin ere antzekoa gertatuko litzateke, egokitasun kontzeptu ezberdinak erabiliaz.

Sakonago aztertu aurretik iturri bakoitza, LNParen bi eskola nagusietako ukitua ikusiko dugu hemen ere: tradizionala edo sinbolikoa, eta corpusetan oinarritutako estatistikoa. Ebazpen estatistikoak hedatuagoak daude literaturan, gure ustez arrazoi nagusi batengatik: testu errealekin lan egiteko hobeto prestatuta daudelako, estaldura eta sendotasun aldetik batez ere. Aurrera jarraitu aurretik esan beharra dago hurbilpen estatistikoetan ezagutza sintaktiko eta semantikoaren arteko ezberdintasuna lausotu egiten dela sarritan, hitzetan oinarritutako maiztasunak erabiltzen dituzte eta.

Sintaxiari dagokionez nahiz eta esaldien analisi osoa desiragarria litzatekeela aitortu (Kukich, 1992), kategoria etiketa soilekin lan egiten da nagusiki, esaldien egitura sakonago aztertu gabe. Salbuespena Vosse (1994) da, Testuingururik Gabeko Gramatika Hedatuetan (*Augmented Context-Free Gramars*) oinarritutako analisi sintaktiko osoa proposatzen baitu. Nahiz eta bere lana batez ere errore morfo-sintaktikoak zuzentzera zuzendu, ez-hitza erroreen kasuan proposamen bakarra aukeratzen ere saiatzen da. Bere lanean egiten den ebaluazio kuantitatiboa nahasgarria da oso, baina ez-hitza erroreekin lortzen duen doitasuna testu errealetan %60aren inguruan legoke. Testu errealen aurrean doitasuna asko jaisten dela eta, analizatzaile sintaktikoak halakoekin arazoak dauzkala aitortzen du.

Estatistikan oinarritutako lanetan ezagutza sintaktikoa hitz jakin baten inguru hurbilean dauden hitz eta kategoria multzoen kontaketara mugatzen da: kategoria-bigrama eta -trigramak, hitz-bigrama eta -trigramak, eta horien arteko konbinazioak (Gale & Church, 1990; Mays et al. 1991; Golding & Schabes, 1996). Lehenbiziko lanean testuingururik gabe lan egiten zuen sistemari (Kernighan et al. 1990) kategoria-bigrama eta -trigramak gehitzen dizkiote, AP Newswire corpus zabaletik (10^6 hitz) jasotakoak, eta zuzentzailearen doitasuna %87tik %89,7ra igotzen da. (Mays et al. 1991; Golding & Schabes, 1996) lanetan ez-hitzen zuzenketa automatikoa baino harantzago doaz, benetako hitza erroreak detektatu eta zuzendu nahi baitituzte. Golding eta Schabes-en kasuan ingelesez maiz gertatu ohi diren bi hitzen arteko nahasketak aztertzen dituzte (18 bikote guztira), adibidez `wheather/whether` edo `dairy/diary`. Sistemak `dairy` edo `diary` aurkitzen duenean, bere testuingurua aztertu eta errore bat dela erabaki dezake, beste hitzaz ordezkatuz. Ezagutza sintaktikoa bi eratara erabiltzen da: alde batetik kategoria-trigramak erabiliz kategoria egokiena esleituko duen etiketatzailea dago (Mays et al. 1991), eta bestetik hitz/kategoriaz osatutako bigrama eta trigrama nahastuak (Yarowsky, 1994). Etiketatzailea kategoria ezberdina duten hitzen artean erabakia hartzeko gai da (`weather` izena, `whether` konjuntzioa), baina kategoria berdina dutenean ez (`dairy` eta `diary` izenak dira, esneki eta agenda esanahia dutenak). Azkeneko bikotearentzat honako hitz/kategoria trigramak jasotzen du `diary`-ren aldeko ebidentzia:

```
in POSS-DET _
```

Hau da, `dairy/diary`-ren aurrean `in` preposizioa eta edutezko determinantea daudenean `diary` hobetsiko da. Sistema honetan ezagutza sintaktiko eta semantikoa ez daude bereizita, biak era nahasian erabiltzen baitira, eta beraz emaitzak beherago ikusiko ditugu.

Ingels-en (1996; 1997) lanean lehenago aipatutako erroreen iturburuaren eredua eta ezagutza sintaktikoaren eredua konbinatzen dira. Bigarrena kategoria-bigrametan oinarritutako Markoven Eredu Ezkutu (*Hidden Markov Model*) batez egiten du. Ezagutza sintaktikoa erabilitako bi testuei hertsiki lotzen zaie, testu bakoitzarentzat trebatzen baitu bere sistema. Testu berri baten aurrean sistema berriz trebatu beharko litzateke. Emaitzei dagokionez, ezagutza sintaktikoak nabarmen hobetzen ditu emaitzak ez-hitz erroreen kasuan, %89tan ondo zuzentzen baitu lehenbiziko esperimentuan (ezagutza sintaktiko gabe %74) eta %83 bigarrengoan (gabe %54).

V.A.2.c) Semantika

Ezagutza semantikoa erabiltzen duen sistema sinboliko inplementaturik ez dugu ezagutzen, sistema estatistikoak bai ordea. Hauetan ezagutza semantikoa errepresentatzeko agerkidetzak (*cooccurrence*) erabili ohi dira, hau da, testuinguruko N hitzeko leiho batean hitzak zenbat aldiz azaltzen diren kontatzean. Hala egiten dute Golding eta Schabes-ek (1996) sintaxiari buruzko ezagutza (Yarowsky, 1994)-n proposatutakoarekin hedatuz. Goragoko adibidearekin jarraituz honako hau izan liteke `dairy`-ren aldeko ebidentzia semantiko bat:

```
milk ± 10 hitzetako leiho barruan
```

Ezagutza sintaktiko eta semantikoa konbinatuaz 18 bikoterentzat egindako esperimentuetan %70etik %98.9ra doazen doitasunak lortzen dituzte.

Gorago bi aldiz aipatu dugu Yarowsky-ren (1994) lana. Berez ez da testu-zuzenketari buruzkoa, Frantsesera eta espainierako hitzetan azentu egokia jartzeari buruzkoa baizik. Hala ere berak erabilitako ezagutza iturri eta algoritmoak Golding-ek aplikatu zituen (Golding, 1995; Golding & Schabes, 1996) testu-zuzenketan. Informazioa jasotzeko prozedura bera da bietan, aurrerago ikusiko dugun bezala. Ezberdintasun nagusia informazioa konbinatzeko metodoan datza. Yarowsky-k erabakia hartzeko (`dairy/diary`) ebidentzia indartsuena erabiltzen du. Golding-ek, ordea, ebidentzia guztiak konbinatu nahi ditu, emaitza hobeagoak atera nahian. Ebidentziak estatistikoki (Bayes-en erregela medio) konbinatu ahal izateko beraien arteko dependentzia ezabatu beharra dago, eta beraz heuristiko batzuk erabiltzen dira horretarako, nahiko *ad hoc* direnak. Yarowsky-ren metodoa sinpleagoa da, eraginkorragoa konputazioan, eta Golding-en (1995) artikuluan azaltzen denez konbinazioarekin doitasunaren irabazia apala litzateke (batez-beste %81,3tik %82,9ra).

Ezagutza iturrien konbinazioari buruz, beste testuinguru batean Ménèzo-ren taldeak (Ménèzo et al. 1996; Genthial et al. 1994) adimen artifizial banatuan oinarritutako ortografia eta gramatika zuzentzaile bat proposatzen du, ezagutza iturri ezberdinak konbinatzen dituenak. Sistema hau LNP tradizionalaren baitan koka dezakegu, baina nahiz eta sistema interesgarria iruditu, ez du emaitza kuantitatiborik aurkezten.

V.B. Sintaxian eta semantikan oinarritutako zuzenketaren bideragarritasuna

Semantikak proposamen bakarra aukeratzeko orduan egin lezakeen ekarpena neurtzeko bi aurre-azterketa egin genituen, bata euskararako eta bestea frantseserako. Lehenbizikoan, ezagutza sintaktikoarekin bakarrik zuzenketa egokia ezin dela proposatu arrazoitzen da, bigarrenean, IDHS-ren (Agirre et al. 1997) ezagutza-basean dagoen informazioak eta Dentsitate Kontzeptualak oinarri ona eskaintzen dutela.

V.B.1. Euskararen azterketa

Zuzenketarako sistema diseinatu aurretik, sintaxi eta semantikaren ekarpena neurtu nahi genuen. Horretarako euskaraz egindako erroreen corpusa bildu eta ortografia-erroreen azterketari ekin genion (Agirre, 1993). Azterketa honetan ingurune ideal bat aurresuposatu zen, hau da, analisi sintaktiko sendo, oso eta sakona, baita ezagutza semantiko osoa ere. Analisi sintaktikoa pertsona batek simulatu zuen. Ezagutza semantikoa aplikatzeko oinarri izateaz gain, proposamenak baztertzeko bere gaitasuna ere neurtu zen. Adibidez:

```
Laguntza behar dut arazo hau kopontzeko*.

kopontzeko* ⇒ konpontzeko, kopontzako

Laguntza behar dut arazo hau konpontzeko ONDO
Laguntza behar dut arazo hau kopontzako  GAIZKI
```

Adibideko erroreak bi proposamen ditu, lehenbizikoa aditza eta bigarrena izena (kopa izenaren plural hurbila). Lehenbiziko proposamena sintaxi aldetik onargarria da, ez horrela bigarrena.

Semantikari dagokionean ezagutza semantiko tradizionala ere hartu genuen kontuan: hautapen-murrizpenak alde batetik eta erlazio-izera lexikal-kontzeptuala bestetik.

Hautapen-murrizpenak aditz eta adjektiboen argumentuek betebeharrezko ezaugarri lexikalak dira. Adibidez:

```
konpondu [agente:pertsona, objektu:gailu edo faktore kognitibo]

apurtu [agente: animali, objektu: izaki fisiko]
```

Horrek esan nahiko luke konpondu ekintzaren agentea pertsonaren bat izan beharko litzatekeela, eta ekintzaren objektua gailu edo faktore kognitiboren bat. Ezagutza hori erabiliz, errorea argumentu batean ematen denean[62], argumentu horren hautapen-murrizpena betetzen ez dituzten proposamenak errefusatuko dira. Ikusi ditzagun pare bat adibide:

```
Araso* hau konpontzeko eskatu dut.
araso* ⇒ eraso, arazo, arasa, arbaso
       [gailu edo faktore kognitibo] ⇒ arazo, arasa

Lehioa* apurtu da.
lehio* ⇒ lehia, lesio, leiho
       [izaki fisiko] ⇒ leiho
```

62 Hautapen-murrizpenak erabili ahal izateko analisi sintaktikoa behar da, gutxienez aditzaren argumentu nagusienak ezagutuko dituena.

Konpontzen aditzaren subjektua gailu edo faktore kognitibo bat izan behar da, eta *araso*-ren proposamenetatik bi bakarrik betetzen dute murrizpena, arazo eta arasak. Beste adibidean, apurturen objektua izaki fisiko bat izan behar da, beraz *lehioa*-ren proposamenetatik lehia eta lesio bazter daitezke, leiho bakarrik utziz. Hautapen-murrizpenak aplikatu ahal izateko, analisi sintaktikoak aditzaren argumentuak (agente, objektu, eta abar) zeintzuk diren eman beharko digu.

Erlazio-izaera lexikal-kontzeptuala Dentsitate Kontzeptualaren bidez kalkula daiteke (ikusi III. eta IV. kapituluak). Proposamen posible eta testuinguruko izenen arteko Dentsitatea neurtu, eta Dentsitate maximoa duen izena izango litzateke testuinguru horrentzat hurbilena. Adibideko esaldian, *uzain*-en proposamenen eta testuinguruan dauden izenen (ukendu eta erle) arteko Dentsitatea neurtu eta usain-ek edukiko luke Dentsitate maximoa.

```
Ukenduaren uzainak* erlea aldendu zuen
uzainak* ⇒ zainak, usainak
```

$$\max_{x \in \{\text{usain}, \text{zain}\}} \text{dentsitatea}(\{\text{ukendu}, \text{erle}\}, \text{x}) \quad \Rightarrow \quad \text{usain}$$

Testuak Irale programako ikasle batzuei jasoak dira (Maritxalar & Ilarraza, 1996). Euskararen ezagutza maila ertaina denez ortografia-erroreetan oparoa da, baita sintaxi-erroreetan ere. Guztira 48 testu dira, 8.290 hitz. Horietatik Xuxen zuzentzaile ortografikoak 1.022 okertzat jo zituen (nahiz eta 102 ez izan benetako erroreak, adibidez izen propio batzuk), 520 errore proposamenik gabe gelditu ziren, eta 95entzat zuzenketa egokia ez zegoen proposamenen artean[63]. Horrek 305 errore uzten ditu zuzentzeko moduan, baina 123k proposamen bakarra dutenez tratamendua behar dutenak 182 dira (ikusi 16. taula).

[63] Xuxen-en alde esan beharra dago errore batzuk oso gaitzak zirela, eta bestalde azterketa hau egin zenetik (1993) Xuxenen bertsio berriak atera direla.

Testu kopurua	48	
Hitzak guztira	8.290	
Hitz okerrak (Xuxen)	1.022	
Zuzenak	102	
Proposamenik gabekoak	520	
Proposamen zuzenik ez	95	
Proposamenekin	305	
Proposamenak	305	
Proposamen bakarra	123	%40
Proposamen anitz	182	%60
Proposamen anitz	182	
Sintaxia	128	%70
Semantika	54	%30
Semantika	54	
Proposamen bakarra	34	%63
Proposamen anitz	11	%20
Ez du ezer egiten	9	%16

16. taula: euskararako azterketaren emaitzak

Ezagumendu sintaktikoa proposamen bakarra aukeratzeko gai zatekeen erroreen %70ean, baina %30ean proposamen bat baino gehiago utziko lituzke semantikaren esku. Lehenago aipatutako hautapen-murrizpen eta Dentsitate Kontzeptuala erabiliz errore horien %63rako proposamen bakarra aukeratzeko gai izango litzateke, nahiz eta proposamen batzuk ezabatu 2 edo 3 proposamen geldituko lirateke %20an, eta %16an ez da gai proposamenik aukeratzeko.

Semantikari esparru zabala azaltzen zaio

Aurre-azterketa honetatik sintaxiak bere kabuz gehienez erroreen %70a konponduko lukeela erakusten du, nahiz eta analizatzaile sintaktiko perfektua simulatu, eta gogoan izanda euskarak informazio morfosintaktiko asko eskaintzen duela beste hizkuntzekin alderatuz gero. Beraz semantikari esparru zabala geratzen zaio, gutxienez erroreen %30a, eta errore horietatik %63 konpontzera hel daiteke. Sintaxi eta semantika perfektua suposatuz ere errore gutxi batzuk zuzentzeke gelditzen dira. Horietarako beste informazio-iturri batzuk, hala nola, munduaren ezagutza, pragmatika, eta abar hartu beharko lirateke kontuan. Hona hemen azkeneko kasuaren adibide bat:

```
Astoa handia izanez, eta erlia* txikia izanez, …
erlia* ⇒ eria, erlea, erbia, erdia
```

Erlazio-izaera semantikoak eria eta erdia baztertuko lituzke, baina ez dago arrazoirik erlea edo erbia aukeratzeko.

V.B.2. LPPL-ren HEBaren egokitasunaren azterketa

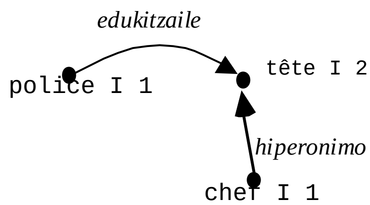
Ezagutza semantikoa beharrezkoa bada, non egongo da jasota ezagutza hori? Zein errepresentazio eredu erabiliko dugu? Ezagutza hori ez badago jasota nondik eta nola eskura dezakegu?

Orain arte bi ezagutza semantiko aipatu ditugu: hautapen-murrizpenak eta erlazio-izaera lexikal-kontzeptuala. Bigarrenerako ikusi dugu Dentsitate Kontzeptuala formalizazio egokia dela, eta nola inplementa daitekeen WordNet ezagutza-basearen gainean (ikus III.C.2 atala). Azter dezagun orain adibide baten bidez nola heda daitekeen Dentsitate Kontzeptuala HEBan dauden hautapen-murrizpenei lotutako informazioa ere integratzeko:

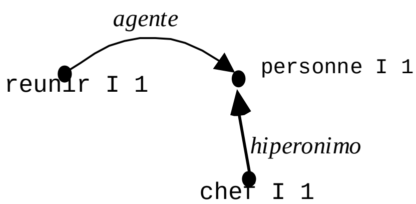
```
Le cheé* de la police ha reunit vingt hommes sur la place du village.

cheé* ⇒ chef, cher, chez, chié, chéri, chic
```

Proposamen eta testuinguruaren artean hainbat erlazio topa daitezke LPPL-ren ezagutza-basean, bai Dentsitate Kontzeptuala aplikatzeko (ikus 23. irudia), bai hautapen-murrizpenak ebazteko (ikus 24. irudia). Bi irudietan azaltzen diren erlazioak LPPL-ko HEBan jada existitzen dira. Aipatzeko da, WordNet-en ez bezala, HEB honetan erlazio paradigmatikoez gain bestelako erlazio asko ere badaudela (adibidez 23. irudiko *edukitzaile*, edo 24. irudiko *agente*, ikus II. kapitulua ere), eta Dentsitate Kontzeptuala horietaz balia zitekeen.



23. irudia: chef eta police-en kontzeptuen arteko erlazioa



24. irudia: reunir-en hautapen-murrizpena chef-ek nola bete dezakeen

Ondorioz, LPPL-tik erauzitako Hiztegi Ezagutza-Baseak zuzenketarako beharrezkoa den ezagutza semantiko hori eskaintzen duela ikusi dugu –honi buruzko argibide gehiagotarako ikus (Agirre et al. 94; Agirre et al. 95)–.

V.B.3. Bideragarritasun-azterketaren ondorioak

Orain arte azaldutakoaren arabera ondorio hauetara iritsi gara:

- Ezagutza sintaktikoa ez da nahikoa (ikus V.B.1 atala).
- Ezagutza semantikoaren erabilera beharrezkoa eta posiblea da, frantseserako eraiki den LPPL-ren ezagutza-baseak erakusten duen bezala (ikus V.B.2 atala).

Ondorioz esperimentu erreal bat prestatzeko arrazoiak badaude. Bestalde, ezagutza iturri hauekin esperimentu errealista bat diseinatzeko orduan hainbat muga agertu zaizkigu:

- Frantseserako HEBaren estaldurak testu librearekin lan egitea galarazten du.
- Hautapen-murrizpenak ez daude jasota ez HEBan[64], ez WordNet-en, ez eta eskuragarri dauden beste ezagutza-base orokorretan ere.
- Analisi sintaktiko osoa egingo digun sistemarik ez dugu eskura. Horrelako sistema beharrezkoa da hautapen-murrizpenak dagozkien hitzei aplikatu ahal izateko.

Muga hauek bultzatu gintuzten esperimentu erreala ingeleserako prestatzen, estaldura zabaleko WordNet gainean Dentsitate Kontzeptuala erabiliz, baina hautapen-murrizpenik eta erlazio ez-paradigmatikorik gabe. Bestalde, corpusetan oinarritutako hainbat teknikek ere nolabaiteko ezagutza semantikoa isladatzen dutenez (Yarowsky, 1994; Golding & Schabes, 1996), horrelakoak ingeleserako corpus zabal batetik eskuratzea ere bideragarritzat jo genuen.

V.C. Erabilitako teknikak

Semantika kontuan hartzen duten teknikez gain, ezagutza sintaktikorako Murrizpen-gramatika erabili da, eta eskura egon zitezkeen beste heuristikoak ere ez dira baztertu. Tamalez hitz isolatuen zuzenketarako eredurik ezin izan genuen eskuratu. Hauek dira erabili ditugun teknikan.

V.C.1. Murrizpen-gramatika (MG)

Murrizpen-gramatika testu librearen analisi sintaktikorako sortu zen, sendotasun eta estaldura zabala helburu. Hainbat hizkuntzatan aplikatu bada, euskara barne, ingeleserako kategoria etiketatzaile bezala eduki du arrakasta handiena (Karlsson et al. 1995). Guri dagokigunean, Murrizpen-Gramatika izango da proposamenak aukeratzeko izango dugun ezagutza sintaktikoa.

V.C.2. Dentsitate Kontzeptuala (DK)

Ezagutza semantikoa WordNet gainean lan egingo duen Dentsitate Kontzeptualak emango digu (ikus III.B atala). Honen arabera, proposamen guztiak izenak direnean, beraien artean

[64] HEBan hautapen-murrizpenak erauzteko beharrezko ezagutza egon badago, aurreko ataleko adibideak erakusten dutenez, baina ez dira oraindik fisikoki erauzi.

testuinguruarekiko Dentsitate altuena duena aukeratuko genuke. Dentsitate Kontzeptuala adieren arteko neurria izanik, Dentsitate altueneko adiera duen izena aukeratzen da. Dentsitatea neurtzeko orduan inguruko 60 izen hartu dira testuinguru bezala, hitzen adiera desanbiguazioan emaitza onenak lortu diren berak.

V.C.3. Maiztasuna (BM eta DM)

Bi maiztasun jaso dira: hitzen maiztasun orokorra, Iparramerikako ingeleserako estandar bilakatu den Brown corpusetik hartua (Francis & Kucera, 1967), eta dokumentuan bertan dauden hitzen maiztasuna. Lehenbizikoari BM eta bigarrenari DM deitu diegu.

V.C.4. Testuingurua kontuan hartzen duten metodo estatistikoak (TS)

Yarowsky-ren lana (1994) hartu genuen oinarritzat (ikus lan honi buruzko oharrak IV.A.4 atalean). Bere lanean ez bezala gurean ezinezkoa da aldez aurretik proposamenen multzoa mugatzea, errorea edozein hitzetan azaldu daiteke eta (ikus V.A.2 atala). Hori dela eta maiztasun gordinak fitxategietan gorde eta proposamenak zuzentzeko orduan kalkulatuko dira beharrezko neurriak.

Maiztasun informazioa bildu ahal izateko, lehenbizi Brown corpusa tokenizatu eta ondoren bigramak, trigramak eta leiho jakin baten[65] agertzen diren hitz pareak fitxategi batzuetan gorde dira, bakoitzaren agerpen kopurua zenbatuta dagoela. Gure kasuan ez kategoriak ezta lemak ere ez genituen erabili, hitz-formak soilik. Neurri estatistiko bezala log-sinesgarritasuna (*log-likelihood*) erabili dugu, Yarowsky-ren moduan. Log-sinesgarritasuna erabiltzearen abantaila, erabakia topatutako ebidentzia indartsuenaren arabera hartzea da. Beste neurriekin ebidentzia guztiak konbinatu behar dira prozesu garestiago batean, prozesu guztia motelduz abantaila gehiegirik atera gabe (ikusi V.A.2 atala).

V.C.5. Bestelako heuristikoak (H1 eta H2)

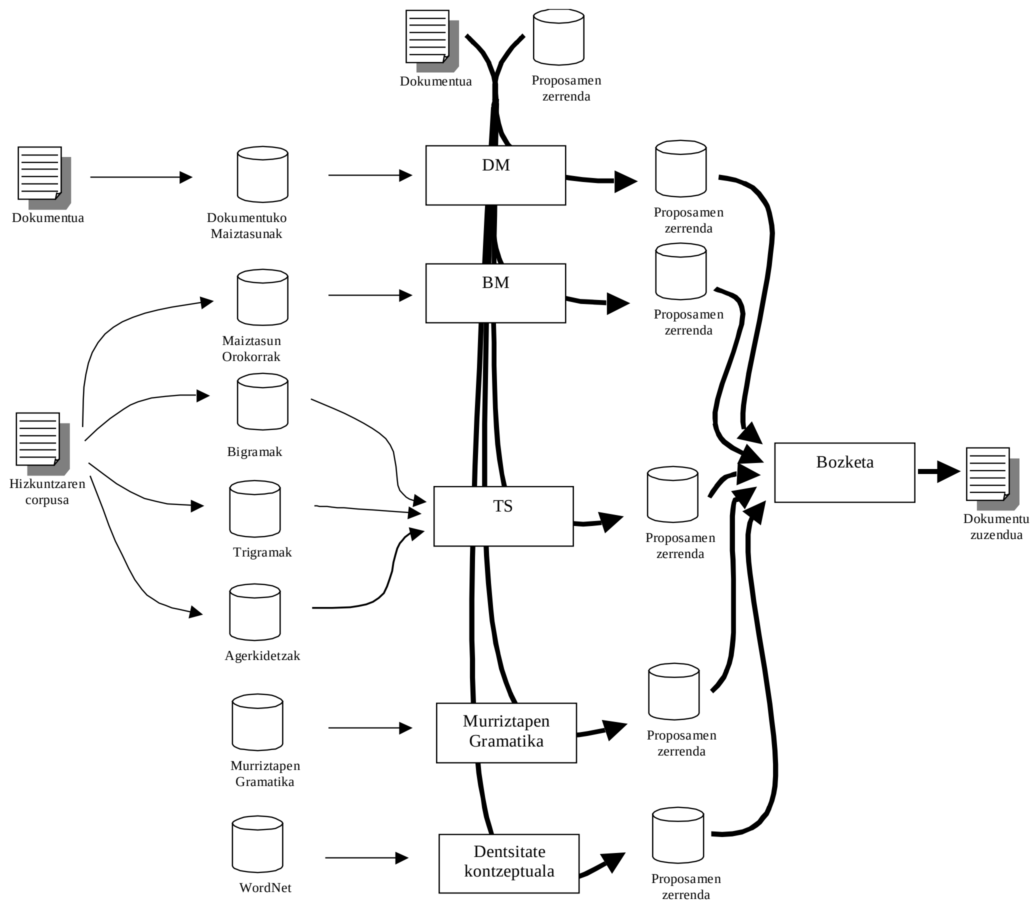
Esperimentuak egin ahala heuristiko sinple batzuen beharra ikusi genuen. Alde batetik sarritan proposamenen artean izen nagusiak agertzen zirela igarri genuen, nahiz eta errorearen lehenbiziko hizkia xehea izan. Halakoetan izen nagusiak ziren proposamenak arazo gabe ezaba zitezkeen (H1 heuristikoa).

Beste aldetik, ingelesez hiruzpalau letratako erroreetarako proposamenak ugariegiak suertatzen dira. Sistemaren doitasuna errore labur horietarako erantzunik eman gabe hobetuko zelakoan geunden (H2 heuristikoa).

[65] . Leihoaren zabalera 40 hitzetakoa izan da.

V.C.6. Konbinazioa: bozketa

Lau metodo eta bi heuristiko sinple ikusi ditugu. Teknika heterogeneoak direnez ez da erreza aurrikustea zein izango den denak konbinatzeko sistemarik hoberena. Hori dela eta 5 teknikentzat VI.D.7 atalean erabilitako sistema bera erabiliko dugu: bozketa. H1 heuristikoak ez duenez kale egiten beti aplikatu izan dugu, H2 ez ordea. Sistema osoaren eskema 25. irudian ikusi daiteke.



25. irudia: proposamenaren hautapenerako ezagutza iturriak eta konbinatzeko sistema

V.D. Ingeleserako esperimentuak

Teknika bakoitzak pisu ezberdina eduki dezakeenez bozkatzerako orduan, teknika eta pisuen aukeraketa esperimentua egiten genueneko testuari lotua ez egotea lortu behar genuen. Horretarako konbinazio guztiak lehenbiziko corpus baten gainean probatu eta onenak aukeratu genituen. Aukeratutako konbinazio horiek beste corpus ezberdinean probatu ziren, emaitzak baieztatzeko.

V.D.1. Aukeratutako corpusak: sortutako erroreak eta benetako erroreak

Bi corpus aukeratu genituen esperimenturako. Alde batetik Brown corpuseko dokumentu batzuetan errore artifizialak sortu genituen ausaz, eta bestetik benetako erroreak zeuzkan testuak bildu genituen. Lehenbizikoan erroreen zuzenketa zein den automatikoki jakin dezakegunez, nahi bezain handia egin dezakegu, eta beraz berebizikoa da saiakera ezberdin asko egiteko. Bigarrenak aldiz, benetako testu baten aurrean espero genezakeen emaitzaren berri emango liguke.

Lehenbizikorako 8 bertsio egin genituen. Damerau-ren (1964) legeak jarraituz batez-beste 20 hitzetan behin errore bat sortzen duen *antispell* programa (lan honetarako espreski garatua) 8 aldiz egikaritu genuen aldez aurretik aukeratutako Brown corpuseko lagin baterako. Corpus honi *artifiziala* deituko diogu. Bozketa-saiakera ezberdinak egin ahal izateko, aipatu bezala, corpus hau bitan zatitu zen: zati baten lau testu eta bestean beste lauak (ikusi datuak 17. taulan).

Benetako erroreak dituen corpusa, *benetako* corpusa, *Bank of English* delako corpusetik aldizkarien testuak bilduz jaso genuen. Hauetarako bai, eskuz erabaki izan behar genuen zein zen errore bakoitzaren zuzenketa.

	1. erdia	2. erdia	benetakoa
Hitzak	47.584	47.584	39.733
Topatutako erroreak	1.354	1.403	519
Proposamendun erroreak	1.354	1.403	369
Ispell-en proposamenak	7.242	8.083	1.257
Proposamen anitzeko erroreak	810	852	158
Erroredun hitz luzeak (H2)	968	980	331
Hauentzako proposamenak (H2)	2.245	2.313	807
Proposamen anitzekoak (H2)	430	425	124

17. taula: errore corpusen datuak.
Lehenengo bi zutabeak corpus artifizialari dagozkio.

Bi corpus hauek *ispell* izeneko ingeleserako zuzentzailetik pasatu genituen. Corpus artifizialerako arazo gabe topatu zituen erroreak eta sortu proposamenak. Benetako corpusean arazoak izan zituen, 150 hitzentzat ez baitzuen proposamenik sortu (gehienak izen bereziak edo hitz arrotzak). Guztira 1.354, 1.403 eta 369 errore zeuden corpus bakoitzean, zegozkien proposamenekin. Proposamen bakarrekoak kenduta, 810, 852 eta 158 errore geratu zitzaizkigun tratatzeko. 17. taulan H2 heuristikoa aplikatuz gero, hau da, errore laburrak kontuan hartuko ez bagenitu, gelditzen den errore kopurua ere azaltzen da. Honek ematen digu egin beharreko lanaren neurria. Adibidez, benetako testuan erroreen erdiak baino gehiago proposamen bakarra dauka, eta proposamen anitzeko erroreek batez beste 6,62 proposamen dituzte, errore luzeak soilik kontuan hartuz gero, aldiz, 4,84.

V.D.2. Emaitzak

Ebaluaziorako ondoko hiru neurriak erabili ditugu:

- Estaldura: proposamenen bat aukeratzen den aldi kopurua, hau da, erantzunik ez dagoenean ezik.

- Doitasuna: proposamen-aukeraketa egin denean, zuzena zenbat aldiz geratu den.

- Aukeratutako proposamenak: batez-beste zenbat proposamen aukeratu izan diren errore bakoitzeko.

V.D.2.a) Konbinazio hoberenen bilaketa

Esan bezala, corpus artifizialaren erdian egin genituen lehenbiziko saioak. 18. taulan azaltzen dira teknika bakoitzerako lortutako emaitzak, hala nola konbinazio arrakastatsuenen emaitzak, beti ere proposamen anitz dituzten erroreentzat, hau da, proposamen bakarrekoak kontuan eduki gabe. Horiek kontuan edukiko balira emaitzak hobeak lirateke, noski, baina okerrago adieraziko lukete teknika bakoitzaren eraginkortasuna. Teknika isolatuen artean DM eta TSek lortu zituzten emaitza aipagarrienak (taulan ilun azaltzen direnak), denak ere ausaz lortuko liratekeen emaitzak erraz gaindituz. DKak lortzen ditu emaitza apalenak, estaldura aldetik batez ere, kasuen %8an bakarrik baita erantzuteko gai. Aurrerago aztertuko dugu hori.

Konbinazioen artean gutxi batzuk erakusten ditugu, hoberenak ilun azaltzen diren MG1+DM1+TS1 eta MG1+DM1+TS2 dira, hau da, Murrizpen-Gramatikak botu bat, Dokumentuko Maiztasuna botu bat eta Testuinguruko Estatistikek botu bat edo bi jasotzen dituzteneko konbinazioak, hurrenez hurren. Doitasun gorena beraz %86koa da, estaldura ia osoaz, eta 1.12 proposamen utziaz batez beste.

Hitz luzeak bakarrik zuzentzen ahaleginduz gero (H2) orduan estaldura ia erdira jaisten da, doitasun kasu onenean (MG1+DM1+TS1+H2) %92raino heltzen delarik 1,11 proposamen utziaz.

	%Estal.	%Doi.	#prop
Oinarrizko teknikak			
Ausazkoak	100,00	23,70	1,00
MG	99,75	78,09	3,23
DK	8,27	75,28	1,01
BM	93,70	76,94	1,00
DM	84,20	81,96	1,03
TS	94,48	84,94	1,02
ausazkoak+H2	52,70	36,05	1,00
MG+H2	52,57	90,68	2,58
BM+H2	48,04	81,38	1,00
DM+H2	38,48	89,49	1,03
TS+H2	47,79	89,77	1,02
Konbinazioak			
MG1+DM2	99,88	83,93	1,28
MG1+DM1+BM1	99,88	81,83	1,04
MG1+DM1+BM1+DK1	99,88	81,83	1,04
MG1+DM1+TS1	99,88	86,45	1,12
MG1+DM1+TS2	99,88	85,45	1,07
MG1+DM2+H2	52,70	91,86	1,43
MG1+DM1+BM1+H2	52,70	88,14	1,06
MG1+DM1+BM1+DK+H2	52,70	87,91	1,05
MG1+DM1+TS1+H2	52,70	92,12	1,11
MG1+DM1+TS2+H2	52,70	90,32	1,09

18. taula: proposamen anitz duten erroreetarako emaitzak (1. erdia).

	%Estal	%Doi	#prop
Oinarrizko teknikak			
Ausazkoak	100,0	23,71	1,00
DM	84,04	81,42	1,03
TS	95,39	84,90	1,02
Ausazkoa+H2	50,12	34,35	1,00
DM+H2	36,32	87,66	1,04
TS+H2	46,93	86,35	1,02
Konbinazioak			
MG1+DM2	99,41	83,59	1,31
MG1+DM1+BM1	99,41	79,81	1,05
MG1+DM1+BM1+DK1	99,41	80,05	1,05
MG1+DM1+TS1	99,53	86,14	1,15
MG1+DM1+TS2	99,53	85,26	1,07
MG1+DM2+H2	50,12	90,12	1,50
MG1+DM1+BM1+H2	50,12	84,24	1,06
MG1+DM1+BM1+DK+H2	50,12	84,47	1,06
MG1+DM1+TS1+H2	50,12	88,70	1,16
MG1+DM1+TS2+H2	50,12	86,59	1,07

19. taula: proposamen anitz duten erroreetarako emaitzak (2. erdia).

V.D.2.b) Konbinazio hoberenen egiaztapena

Behin konbinazio hoberenak zeintzuk izan zitezkeen zehaztu eta gero, corpus artifizialaren bigarren erdiarekin probatu genituen. 19. taulan ikusten den bezala emaitzak mantendu ziren, nahiz eta kuantitatiboki zertxobait jaitsi orokorrean. Honek frogatzen du konbinazio hoberenak orokorrak direla, ez daudela corpusari lotuta.

V.D.2.c) Benetako erroreen corpusa

Artifizialki sortutako erroreek emaitzak baldintza zitzaketelakoan, benetako erroreen corpusaren gainean probatu genituen konbinazio hoberenak, bai eta oinarrizko teknikak ere[66]. 20. taulako emaitzek adierazten duten bezala, konbinazio hoberenak mantendu egiten dira, baina doitasun eta proposamen kopuruak dezente okertu. Horrela puntako doitasuna H2 erabili barik %78koa da (8 puntu gutxiago) 1,56 proposamen utziz, eta H2 erabilita %81 (11 puntu gutxiago) eta 1,53.

Oinarrizko teknika guztien beherakada ikusita ere, bereziki aipagarria da Dokumentuen Maiztasunarena (50 puntu gutxiago estalduran, 20 puntu gutxiago doitasunean, ikusi 18. eta 20. taula). Hau ez da harritzekoa, izan ere benetako corpuseko dokumentuak motzak dira oso, batez beste 50 hitzekoak.

[66] Dentsitate Kontzeptualarekin ez ginen saiatu, bere estaldura (%8) eta benetako errore kopurua (158) txikiak izanik, ondorioak ateratzeko lagin txikiegia zelakoan.

Jaitsiera orokorraren arrazoiak erroreen izaeran bertan egon daitezke, benetako erroreak artifizialak baino zailagoak suertatu direlako edo. Bestalde aipatu beharra dago dialektoen arteko gatazka baten aurrean ere egon gaitezkeela, Brown corpusa Estatu Batuetako ingelesez eta *Bank of English* Bretainia Handikoaz daude eta.

	%Estal.	%Doi.	#prop.
Oinarrizko teknikak			
Ausazkoak	100,00	29,75	1,00
MG	98,10	62,58	2,45
DM	30,38	62,50	1,13
BM	96,20	54,61	1,00
TS	93,21	74,16	1,05
Ausazkoak+H2	76,54	34,52	1,00
MG+H2	75,93	73,98	2,52
DM+H2	12,35	75,00	1,05
BM+H2	72,84	60,17	1,00
TS+H2	67,28	75,36	1,03
Konbinazioak			
MG1+DM2	100,00	70,25	1,99
MG1+DM1+BM1	100,00	55,06	1,04
MG1+DM1+TS1	100,00	78,51	1,56
MG1+DM1+TS2	100,00	75,94	1,09
MG1+DM2+H2	76,24	75,81	2,15
MG1+DM1+BM1+H2	76,54	59,68	1,05
MG1+DM1+TS1+H2	76,54	81,58	1,53
MG1+DM1+TS2+H2	76,54	78,11	1,08

20. taula: proposamen anitz duten erroreetarako emaitzak (benetako corpusa)

	%Estal.	%Doi.	#prop.
Oinarrizko teknikak			
Ausazkoak	100,00	69,92	1,00
MG	99,19	84,15	1,61
DM	70,19	93,05	1,02
BM	98,37	80,99	1,00
TS	97,02	89,10	1,02
Ausazkoak+H2	89,70	75,47	1,00
MG+H2	89,43	90,30	1,57
DM+H2	61,52	97,80	1,00
BM+H2	88,08	85,54	1,00
TS+H2	85,64	91,50	1,01
Konbinazioak			
MG1+DM2	100,00	87,26	1,42
MG1+DM1+BM1	100,00	80,76	1,02
MG1+DM1+TS1	100,00	90,80	1,24
MG1+DM1+TS2	100,00	89,70	1,04
MG1+DM2+H2	89,70	90,94	1,43
MG1+DM1+BM1+H2	89,70	84,89	1,02
MG1+DM1+TS1+H2	89,70	93,10	1,20
MG1+DM1+TS2+H2	89,70	91,80	1,03

21. taula: emaitza orokorrak (benetako corpusa).

V.D.3. Ebaluazioa

Oinarrizko teknikei dagokionez, emaitzek ondoko ondorioetara garamatzate:

- Murrizpen-Gramatika ez da espero zitekeen bezain bikaina, errore dezente sortzen baitu erroredun testuetan aplikatu dugunean (%62ko doitasuna bakarrik benetako corpusean).
- Dentsitate Kontzeptualaren emaitzak apalak dira. Proposamen guztiak izenak izan behar direnez, erroreen %8an bakarrik aplikatu ahal izan da.
- Brown Maiztasuna ez da batere eraginkorra.
- Dokumentuko Maiztasunak emaitza onak lortzen ditu, testuak motzegiak ez badira (benetako corpusaren kasuan gertatu den bezala).
- Testuinguru-Estatistikak dira zalantzarik gabe emaitza hoberenak lortzen dituztenak, estaldura, doitasun eta proposamen kopuruari dagokionean.

Teknika ezberdinen bozketa bidezko konbinazioari esker Testuinguru-Estatistiken emaitzak hobetzea lortzen da, doitasun gorena eta erabateko estaldura lortuz. Horretarako MG, DM eta TS teknikak konbinatzea nahikoa da. Besteen laguntzak ez du emaitza ezertan hobetzen. H2 heuristikoa erabilgarria da doitasuna altxatzeko, baina estaldura %76ra jaisten da.

Sistemaren irteera zein izango litzatekeen neurtzeko proposamen bakarreko erroreak ere kontuan hartu behar dira (ikusi 21. taula). Datu horien arabera bi irteera planteatu daitezke:

- Erabateko estaldura, %90eko doitasuna, eta proposamen bakarra 25 erroretik 24tan (MG1+DM1+TS2).
- Doitasun gorena, %93, baina %90eko estaldura eta proposamen bakarra 5etik 4tan (MG1+DM1+TS1+H2).

Tekniken ekarpenaren azterketa egitean, metodo tradizionalen aurrean, metodo estatistikoak portaera hobeagoa eduki duela ikusi dugu, bai doitasun eta bai estaldura aldetik ere. Murrizpen-Gramatikaren bidez proposamenak baztertzean erantsitako errorea %38koa bada, Dentsitate Kontzeptualak doitasun hobea lortzen du, %75ekoa corpus artifizialean, baina estaldura oso apalaz. Sintaxi, semantika eta kolokazioei buruzko informazioa jasotzen duten Testuinguru-Estatistikek erraz gainditzen dute beste bi horien konbinazioa, zalantzarik gabe.

Dentsitate Kontzeptuala eta Testuinguru-Estatistiken emaitzen arteko aldea argitzeko, lehenbizi DK proposamen guztiak izenak direnean bakarrik aplika daitekeela aipatu behar da. Doitasunari dagokionez DKak ez du testuinguruan agertzen diren izenen taxonomiari buruzko informazioa besterik. TSek ordea corpusetik erauzitako informazio inplizitu aberatsa daukate, bai kategoria ezberdinen artekoa, baita taxonomikoa ez den ezagutzari buruzkoa ere.

Testuinguru-Estatistiken emaitzak, hala ere, Yarowsky-k (1994) kontatzen dituenak baino dezente apalagoak dira. Nahiz eta guk kategoria eta lemak ez erabili, arrazoi nagusiena berak maiz gertatzen diren nahaste-multzo (*confusion-set*) gutxi batzuentzat ebaluatzen duela izan daiteke. Gure kasuan aurrikusi ezin daitezkeen erroreentzat proposamena aukeratu beharra dago, nahiz eta proposamenen horientzako maiztasunak oso baxuak izan (III.D.1 atalean azaldu zaigun datu urrien arazoa). Honek, noski, erabakiaren fidagarritasuna erabat mugatzen du. Arazo honek ez dauka ebazpen errazik. Proposamen batzuek maiztasun baxua dutenez, pentsatu daiteke corpus handiagoak erabilita horien maiztasuna igoko dela. Praktikak erakusten digu hori ez dela zehazki horrela, hitz berriak azalduko zaizkigu eta. Hiztegia ez da zerrenda mugatu bat, are eta corpus handiagoak bildu, orduan eta hiztegi zabalagoak beharko ditugu. Horrela diote Church eta Gale (1990) beraiek:

> *One might think that the sparse data problem could be solved by collecting larger corpora, but ironically, the problem gets worse as we look at more data. The vocabulary is not fixed: both N - size of corpus - and V - size of vocabulary - grow as we look at more data. The rate of growth is still a matter of debate, but the evidence shows that* $V > O(\sqrt{N})$*, and therefore, the sparse data problems only get worse as we look at more and more data.*

Arazo honetaz gain, zuzenketa edozein errorerentzat egin nahi izatean errepresentazio- eta erabilgarritasun-arazoa ere azaleratzen dira. Alde batetik datu gordinak gorde behar direnez (horietako asko ezertarako ere balioko ez dutenak) fitxategi erraldoiak sortzen dira[67] (datu gehiegizkoen arazoa, ikus III.D.1), erabiltzeko motelak. Bestetik, datu gordinak izanda, erabili nahi diren bakoitzean prozesatu beharra dago, behin eta berriz errore bakoitzerako.

Datu horietatik abiaturik maila jasoagoko errepresentazioa sortu beharko litzateke, erabilgarriagoak izateko, eta arrazonamendu ezberdinen euskarri izan ahal izateko. Ezagutza-baseak aberasteko erabiliko balira, adibidez, jatorri ezberdinetako ezagutza integratuko litzateke, eta erlazio mota berriak erantsi. Honek erlazio mota eta kopuru zabaleko ezagutza-base belaunaldi berri bat ekarriko luke, automatikoki erauzitako datuek osatuta. Aipatu dugun bezala, Dentsitate Kontzeptualaren ahulezia ez dago formulan, kontzeptuan. Bere gabeziak lotutako ezagutza-basearen gabezien ispilu dira. LPPL HEBra lotzen badugu erlazio mota aberatsa ustia dezake, baina lexiko eta erlazio kopuru aldetik estaldura eskasa edukiko du. WordNet erabiltzen badugu, lexiko aberatsa edukiko du eskura, eta hiperonimia erlazioa era sakonean landuta, baina beste erlazio motarik ez dago. Corpusetako informazioarekin aberastutako ezagutza-basea izanez gero, Dentsitate Kontzeptualak gaur egun Testuinguru Estatistikek duten ondasun gordin hori guztia ustiatu ahal izango luke.

V.E. Ekarpena

Kapitulu honetan Dentsitate Kontzeptuala aplikazio erreal batean probatu dugu. Alde batetik zuzenketa automatikoa gaur egungo teknologiaren eskura dagoela frogatu dugu, eta bestetik Dentsitate Kontzeptualaren ekarpena apala izan dela ikusi dugu.

[67] Brown corpuseko hitz formentzat: bigramen fitxategiak 10 Mega, trigramenak 41 Mega, zabalera 8 duen lehioko agerkidetzak 42 Mega eta 40rako leihoak 168 Mega. Yarowsky-k (1994) gomendatzen duen leiho zabalera 100ekoa da, eta hitz-formez gain kategoria eta lemak ere barne egon beharko lukete.

Testu-zuzenketa automatikoa egiten duen sistema diseinatu eta eraiki dugu, ez-hitz motako sakatze erroreentzat proposamen egokia aukeratzen dena. Hasierako azterketa batean, ikasleen testu batzuk bildu eta baliabide osoak suposatuz ere, sintaxia soilik proposamen bakarra aukeratzeko gai ez dela ondorioztatu genuen. Semantikaren ekarpena ezinbesteko ikusi genuen, beraz, erlazio-izaera lexikal-semantikoaren eta hautapen-murrizpenen bidez gauzatuko zena. LPPL-ko HEB frantseserako zuzenketa automatikoa egiteko baliabide egokia litzatekeela ikusi dugu, baina lexikoaren estalduraren aldetik arazoak direla eta, esperimentu errealista batetarako ez zegoela prest iritzi diogu. Baliabide zabalagoen bila ingeleserako WordNet aukeratu dugu, baina kasu honetan ez du eskaintzen hautapen-murrizpenei buruzko informaziorik, eta erlazio-izaera kontzeptuala erlazio paradigmatikoetara mugatzen da.

Ondoren, ingelesaren zuzenketa automatikorako sistema aurkeztu da, *ispell* zuzentzaileak topatzen dituen erroreentzat (*ispell*-ek proposamenak sortzeko oso zehatza dela erakutsi digu) proposamen bakarra aukeratzen saiatzen dena. Sistema honek ezagutza-mota ezberdinak konbinatzen ditu: sintaktikoa (Murrizpen-Gramatikak), semantikoa (Dentsitate Kontzeptuala), hitzen maiztasunak, testuinguru-estatistikak eta heuristiko espezifikoak. Murrizpen-Gramatika, Dokumentuko Maiztasun eta Testuinguru-Estatistikei esker, gai da 25 erroretatik 24etan proposamen bakarra aukeratzeko (bestela bi proposamen) %90eko doitasunarekin, eta errore **guztientzat** erantzuten du. Emaitza hauek frogatzen dute zuzenketa automatikoa egingarria izan daitekeela.

Dentsitate Kontzeptualaren ekarpena eskasa izan da. Hasteko beharrezkoa da proposamen guztiak izenak izatea, eta hori oso gutxitan gertatzen da (erroreen %8 inguru errore artifizialak dituen corpusean). Lagin txiki horrekin, fidagarritasun gutxiko datua izanda ere, %75eko doitasuna lortu da. Ausazkoak lortzen duen %23aren ondoan hobekuntza nabarmena. Kapitulu honetan azaldu dugunez, doitasun eta estaldura hauen arrazoia ez da DKarena berez, erabilitako WordNet ezagutza-basearen gabeziena baizik. Bestalde Testuinguru-Estatistikak erabiltzea erabilgarritasun- eta biltegitze-arazo larriak ditu, eta LNPko beste atazetara egokitzeko orduan ez da berrerabilgarria. Hala ere Testuinguru-Estatistikak biltzen duen datu-nahaspilan erlazio baliagarri asko ezkutatzen dira, eta erlazio horien bidez ontologiak (adibidez, WordNet) aberastuz gero aurrerapauso ederra emango zitekeen ontologien eraikuntzan, eta Dentsitate Kontzeptualak gaur egun Testuinguru Estatistikek duten ondasun gordin hori guztia ustiatu ahal izango luke.

V.F. Etorkizunerako lana

Esperimentua diseinatzeko orduan ez genuen kontuan hartu ikasteko corpusa (Brown) eta probatzekoa (Bank of English) dialekto ezberdinekoak zirenik. Ziurra da arazo honek maiztasun orokorrak erabiltzen dituen heuristikoaren eta Testuinguru-Estatistikak erabiltzen dituenaren emaitzak kaltetu dituela. Komenigarriena Bank of English corpuseko bertako datuetatik ikastea izango litzateke, baina tamalez datu horiek eskuratzeko murrizpen gogorrak daude. Murrizpen hauen ondorioz ere errore errealen corpusak oso testuinguru txikia zeukan errorearen inguruan. Horrek modu erabakiorrean kaltetu du Dokumentuko Maiztasunen teknika, bestela oso indartsua zena. Arazo horiek konpondu ondoren doitasuna nabari hobetuko delakoan gaude.

Sistemak duen zehaztasun mugatuak ez dezan galarazi zuzenketa automatikoa, beharrezkoa da erabilitako ezagutza fintzea. Murrizpen-Gramatika, adibidez, erroreak dituzten testuetara hobeto egokitu daiteke, guk erabili dugun bertsioa ez baitzegoen horretarako diseinatuta.

Dentsitate Kontzeptualak emaitza hobeak lortu ahal izateko beharrezkoa litzateke erlazio paradigmatikoak ez direnak eta hautapen-murrizpenak kodetzea ezagutza-basean, kasu honetan WordNet-en. Horrelako erlazioak erauzteko bi iturri ikusten ditugu:

- Hiztegietako *differentiaren* azterketatik erauzi, hurrengo kapituluan aipatu dugun legez.
- Corpusen azterketatik. Izan ere Testuinguru-Estatistikek darabilten informazio gordinean, modu inplizituan bada ere, erlazio eta hautapen-murrizpenak ere ezkutatzen dira.

WordNet bezalako ezagutza-basea bi iturri horiekin aberastuz gero, ezagutza-base lexiko ahaltsuagoa litzateke, eta zuzenketa automatikorako beharrezkoa den ezagutza semantikoaren zati nagusia edukiko luke, Dentsitate Kontzeptualak ustiatuko lukeena. Bestalde, Testuinguru-Estatistiketako informazio hori ezagutza-basean integratuz gero, biltegitze- eta berrerabilgarritasun-arazoak hobetuko lirateke, eta inplizituki adierazita zeuden erlazio ugari esplizituki errepresentatuko lirateke ezagutza-basean, LNPko beste eginbeharretarako prest.

Bukatzeko, III. kapituluan aipatu dugun Dentsitate Kontzeptualaren ezaugarrietako bat kolokan gelditu zaigu. Nahiz eta Dentsitate Kontzeptualaren ezaugarrien artean hitzen arteko erlazio-izaera neurtzeko baliagarria izatea jarri, kapitulu honetako emaitzek zalantzan jartzen dute modu egokian erabili ote dugun. Esperimentu honetarako erabili dugun algoritmoan proposamenen adieren arteko Dentsitate handiena zuen hitza hautatu dugu, baina bestelako konbinazioak ere probatu beharko genituzke, adibidez, hitz bakoitzaren adiera guztien Dentsitatea batu eta batura handiena duen hitza aukeratu proposamen egokia bezala.

VI. Kapitulua
HIZTEGI EZAGUTZA-BASEAREN ABERASKETA

Jadanik azaldu zaigu, aurreko kapituluetan, erlazio-izaera neurri on bat edukitzeko eta Hitzen Adiera-Desanbiguazioa (HAD) egiteko, zein garrantzitsua den baliabide lexikal egituratu aberatsak edukitzea. Hori izango da hain zuzen ere kapitulu honen gaia. Aurre egingo diogun eginkizuna frantses hiztegi bateko adierak WordNet-i lotzea eta hiztegi horretatik erauzitako HEBko hierarkiak desanbiguatu eta sendotzea izango da. Lehenbiziko sailean gaia kokatuko dugu, aurrekariak aztertuz eta gure hurbilpena aurkeztuz. VI.B. atalean hierarkien eraikuntzak dauzkan arazoei buruz ihardungo gara, ziklo eta erlatore bidezko definizioak nola tratatu ditugun azalduz. Hurrengo atalean LPPL-tik erauzitako HEBko adiera eta WordNet-eko kontzeptuen arteko lotura nola egin dugun aurkeztuko dugu. Erabilitako algoritmoak eta lortutako emaitzak ere eztabaidatuko ditugu ebaluazioa egin aurretik. VI.D. atalean hierarkiak aberastu eta trinkotzeko berebiziko garrantzia duen genus-desanbiguazioari buruz arituko gara, emaitzak eztabaidatu eta ebaluazioa ere aurkeztuz. Ondoren, VI.E. Atalean, HEBaren hierarkiak sendotzeko beste prozesua azaldu eta ebaluatuko dugu, hierarkien goiko geruzaren osatzeari buruzkoa. Bukatzeko kapitulu honetan egindako ekarpenak eta etorkizunerako lanak agertzen dira.

VI.A. Aurrekariak eta planteamendua

Kapitulu honetan erlazio-izaera paradigmatikoa beste eremu batean aplikatzen saiatuko gara, hiztegietako ezagutzaren erauzketan hain zuzen ere. Tesi honen helburu nagusietako bati, ingelesa ez diren baliabide lexikal egituratuen eraikuntza sendotzeko teknikak lantzeari, erantzuten dio. 80ko hamarkadan, ordurarteko sistemek lexiko irrigarriak erabiltzen zituztela eta, laborategietako jostailuetatik bizitza errealeko lexikoak eraikitzera pasatzeko beharra nagusitu zen (Boguraev &

Briscoe, 1989a). Lexikoen eraikuntzak, ordea, pentsatzen zena baino giza-ahalegin handiagoa eskatzen zuela ohartuaz, bide automatikoen erabilerara jo zen. Non bilatu ezagutza lexikala, ordea? Hiztegietan, noski. Garai horretan hasi ziren hedatzen hiztegietatik abiatuta Ezagutza-Base Lexikalak (EBL) eta Hiztegi Ezagutza-Baseak (HEB) eraikitzeko ahaleginak, gaur egun ere jarraitzen dutenak. Eremu zabal honetan ez dugu sakonduko hemen, baina hiztegietatik erauzitako informazioari egotzi izan zaizkion bi muga bai aztertuko ditugula, kapitulu honetako gaia izango dira eta:

1. EBL eta HEBen bizkarrezurra diren hierarkiak desanbiguatu gabe egotea
2. Hierarkia horiek txikiak, kalitate gutxikoak eta goi mailan koherentzia gutxikoak izatea

Guk landu dugun hiztegia *Le Plus Petit Larouss* (LPPL) hiztegia da, II. kapituluan aurkeztu duguna. LPPL hiztegiaren gainean egindako lanen ebaluazioak –ikus II. kapitulua eta LPPL-ren inguruan egin dugun lanari buruzko artikuluak (Artola, 1993; Agirre et al., 1994a; 1994c; 1994d; 1997)– erauzitako HEBaren egungo egoeraren ahulezia batzuk planteatu zituen, eta lau alorretan hobetu beharra aitortu genuen:

1. HEBaren hierarkia trinkotzea
2. Adierazpidearen aberasketa
3. Argumentu tipiko eta hautapen-murrizpenen erauzketa
4. Erlazio berriak inferitzeko erregelak

Tesi honetan lehenbiziko puntua landuko dugu. Alde batetik genus gehienak desanbiguatu gabe daude, eta beraz kontzeptuen taxonomian anbiguotasun handia dago. Beste aldetik hierarkia txiki anitz daude, bata bestearekin lotu gabe daudenak.

Hierarkia trinkotzeko egin dugun ahalegina aztertu aurretik, gai honetako aurrekariak aipatuko ditugu.

VI.A.1. Hierarkia-eraikuntza

LNPrako lexikoiak eraikitzeko orduan hiztegiak oinarri sendoa zirela, 80ko hamarkadan bultzada hartu zuen ideia da. Bultzada hori, hasiera batean Amsler-ek (1981) eman zuen, eta ondoren bi hiztegiren azterketa sakonetan gorpuztu zen: *The Webster's Seventh New Collegiate Dictionary* (W7, Gove, 1969) eta *Logmans Dictionary of Contemporary English* (LDOCE, Procter, 1978). Batzuen ahaleginak sintaxiari buruzko informazioaren erauztera aplikatu baziren ere (Boguraev & Briscoe, 1987), hiztegien analisiaren ekarpen nagusia hiztegietan gordeta zegoen egitura semantikoa eskuratzeko saiakerak izan dira (batzuek aipatzeagatik, Michiels & Nöel, 1982; Calzolari, 1983; 1984; Chodorow et al., 1985; 1988; Markowitz, 1986; Binot & Jensen, 1987; Byrd et al., 1987; Byrd, 1990; Cohen & Loiselle, 1988; Vossen 1989; Vossen & Serail, 1990; Boguraev & Briscoe, 1989; Wilks et al., 1990; Briscoe et al, 1990; Castellón, 1992; Artola, 1993; Richardson, 1997; Rigau, 1998).

Informazio semantiko ezkutu hori erauzterakoan, definizio-esaldiak idazteko modu finko samarrak egotea izan zen abiapuntua. Horietako garrantzitsuena Aristotelerengandik ezaguna den *genus* eta *differentia specifica* bidezko definizioa. Definitzen ari garen kontzeptuaren mota edo klasea ematen digu genusak, eta differentiak mota horretako beste kontzeptuetatik bereizteko ezaugarriak. Idazteko modu finko horien arabera, definizioen sailkapena hiru multzotan egin daiteke[68] (Artola, 1993):

- Sinonimo bidezko definizioak
- Genus eta differentia motakoak
- Oinarri-sarrera batekiko erlazio sintaktiko bidezkoak

Definizio mota bakoitzetik erlazio ezberdinak erauzten dira. Sinonimia eta hiperonimia/hiponimia[69] dira garrantzitsuenak. Hirugarren definizio motan, lexikografoak sarrera definitzeko erlazio sintaktiko bat aukeratu du, guk erlatore-berezi izendatu duguna. Erlazio hori meronimia, instrumentala, etab. izan daiteke (Nakamura & Nagao, 1988; Bruce et al., 1992; Artola, 1993).

Proiektu askoren helburu nagusiena genusaren erauzketa automatikoa edo erdiautomatikoa izan da (Chodorow et al., 1985; 1988; Tsurumaru et al., 1986). Baina hiperonimo-erauzketa baino harantzago joan eta diferentia lantzen duten lanak ere badaude (Ahlswede, 1989; Wilks et al., 1990; Michiels & Nöel, 1982; Castellón, 1992; Artola, 1993; Agirre et al., 1994d; Richardson, 1997).

Genusaren garrantzia hiperonimiaren bidez mota-hierarkiak eraikitzeko balio izatetik datorkio batez ere (Amsler, 1981; Vossen & Serail, 1990). Hierarkiak garrantzitsuak dira, EBLen hezurdura izateagatik, egitura formala eman eta erredundantzia ekiditen dutenak, ezaugarrien herentziaren bitartez (Cohen & Loiselle, 1988; Briscoe et al., 1990).

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[68] Beste sailkapenak ere badira, baina deitzeko moduaz gain, denak datoz bat gutxi gora bera. Vossen-ek (1989) Amsler-en (1981) antzera sinonimoei *cross-reference* bidezkoak, genus motakoei *non-complex genus*, eta hirugarren motakoak bitan sailkatzen zituen: *complex genus* eta *derivational*. *Complex genus* horiei beste autoreek izen ezberdinak eman dizkiete: *function words* (Nakamura & Nagao, 1988), *empty heads* (Chodorow et al., 1985), *disturbed heads* (Bruce et al., 1992) edo erlatore berezi (Artola, 1993).

[69] Lexikografian hala deitu ohi zaio adimen artifizialean klase/azpiklase edo IS-A bezala ezagutzen den erlazioari.

Hiztegietatik erauzitako hierarkiei buruzko kexuak, sakonera gutxikoak izatea (Chodorow et al., 1988; Wilks et al. 1990) eta hierarkia bakarra baino mihiztatutako hierarkiez (*tangled hierarchy)* osatuta egotea izan ohi dira (Calzolari, 1983). Wilks-ek, adibidez, hierarkien mihiztadura eta sakonera apala batez ere hitzen arteko hierarkiak eraikitzeagatik sortzen dela dio. Hitz horiek, genusak, desanbiguatuz gero, kontzeptuen arteko hierarkia edukiko genuke, mihiztadura gehiena desagertuaz eta sakonera-arazoak konpontzeko bidea emanaz (Bruce et al., 1992). Genusa desanbiguatzearen beharra autore gehienek aitortzen dute (Richardson, 1997; Ide eta Véronis, 1994). Adibidez zera diote Ide eta Véronis-ek: "*the undisambiguated hierarchy is unusable because, following the path upwards from saucepan, we find that saucepan can be a kind of leaf, which is clearly erroneous*"..

Baina nahiz eta genusa desanbiguatu, hierarkiei buruzko beste kritikak bere horretan darraite. Horietako nagusiena kontzeptu orokorrak definitzeko lexikografoen irizpide eza izan ohi da (Ide & Véronis, 1994). Horrek hierarkietan bigiztak sortu ohi ditu (lehenagotik ere jakina zena, ikus adibidez Amsler 1981; Chodorow et al. 1985; Vossen & Serail, 1990). Bestalde adiera asko hierarkiaren goialdean gelditu ohi dira, hierarkien arteko homogeneotasun faltak sortuaz. Orokorrean, kritikak hierarkietako goi aldeko adieretan zentratzen dira. Bestalde, hierarkiak hain lauak izatearen arrazoia ia eduki semantikorik ez duten genusen erabileratik dator, ekintza edo modu bezalakoak alegia. Azkenik, eta genusak alde batera utzita, erlatore berezien bidez egindako definizioak hierarkiatik kanpo gelditu ohi dira, edo bestela, adabegi isolatu batetik zintzilik (Bruce et al., 1992).

VI.A.2. Genusen adiera-desanbiguazioa

Esan bezala, hierarkiak erabili eta ezagutza-baseetan antolatzeko, beharrezkoa da genusaren desanbiguazioari ekitea. Aipatutako lan gehienetan, desanbiguazio hori eskuz egin beharko litzatekeela aitortzen dute, nahiz eta kasu batzuetan heuristiko ahul eta estaldura eskasekoak planteatu (Amsler, 1981; Chodorow et al. 1985; Vossen & Serail, 1990). Copestake-ek (1990) LDOCE hiztegiko kode semantikoetan oinarritutako teknika aipatzen du, baina ez du espezifikatzen ezta probatzen ere. Richardson-ek (1997) Microsoft-eko lantaldeak horretan diharduela dio, baina ez du inongo erreferentziarik ematen metodoaren edo egungo egoeraren inguruan.

Mexiko Berriko Unibertsitatean hainbat lan egin zituzten LDOCE-ko genusak automatikoki desanbiguatzearen helburuarekin (Bruce & Guthrie, 1991; Bruce et al., 1992). 1992.eko lanean LDOCE-ko adieren maiztasunak, kode semantikoak eta kode pragmatikoak erabili zituzten. Gainera, algoritmoak genus usu eta oso anbiguo batzuetarako (10 baino gutxiago) sistematikoki kale egiten zuela ikusirik, genus horientzat adiera egokia eskuz aukeratu zuten. Horrelako teknika sinpleekin %90eko doitasuna lortu zuten.

HADan erabilitako teknikak (ikusi IV. kapitulua), batez ere hiztegietan oinarritutako erlazio-izaera erabiltzen dutenak, erabat aplikagarriak izanda ere, ez dira espero zitekeen bezainbat erabili izan. Arrazoia, beharbada, Wilks-ek eta hain heuristiko sinpleekin lortutako arrakasta izango litzateke.

VI.A.3. Hierarkia-trinkotzea

Aipatu ditugu arestian hiztegietatik erauzitako hierarkiei egiten zaizkien kritikak:

1. Hierarkietako bigiztak
2. Hierarkien sakonera apala eta goi mailako homogeneotasun falta
3. Erlatore bereziak hierarkian integratzeko arazoak

Halako arazoen aurrean, Ide eta Véronis-ek (1994) hiztegi ezberdinen arteko hierarkiak lotzea aurrerapauso bat izan zitekeela planteatzen dute, gehiegi sakondu gabe. Literaturan arazo hauen irtenbideak ez dira aipatu, norberak bere modura moldatuko balu bezala, edo arazoekin bizitzen ohitu izan balitz bezala. Salbuespen bat Mexiko Berriko taldeak (Bruce et al., 1992) eginiko lana da. Lan horretan, genusak desanbiguatzeaz gain hierarkiaren eraikuntzan azaltzen diren arazo horiei irtenbide integratu bat bilatzen zaie. Horretarako LDOCE-k dauzkan kode semantikoez baliatzen dira. Kode horiek hierarkia bezala antolatu eta beren ontologiako primitibo semantiko bezala hartzen dituzte. Ohiko hierarkia eraikuntzatik kanpo gelditzen diren kasuetan, hau da, genusak eduki semantikorik ez duenean, zikloak apurtzerakoan eta erlatore bidezko definizioak lotzean, adieren kode semantikoa erabiltzen da primitibo semantikoetara lotzeko. Bestalde, ordura arte loturarik gabe zeuden hierarkiak ere erlaziona daitezke, hierarkia horien erroa primitibo semantikoetara lotuaz. Primitibo semantikoen hierarkiak aterki baten funtzioa egiten du.

VI.A.4. Iturri lexikal eleanitzen arteko lotura

Hiztegi elebakarrek jaso duten arretaren aldamenean, hiztegi elebidunek izan duten ahanztura harrigarria dela esan liteke. Hiztegi elebidunen erabilerari buruzko artikuluak ez dira azaldu 90. hamarkadan ondo sartu arte, salbuespen gutxi batzuk kenduta (Byrd, 1990; Rizk, 1989). Ikerlarien interes falta baino arrazoi praktikoak izan dira gehienetan errudunak, hiztegi elebidun horiek eskuratzeko zailtasunak eta tipografia tratatu beharra alegia.

Hiztegi elebidunen ustiapenean, itzulpenaren inguruko informazioa bera baino, askotan, sarrerei buruzko bestelako informazioa izan da helburua. Kolokazio eta kode semantikoak erauzi izan dira batez ere (Heylen et al., 1993; Helmreich et al., 1993), eta berriki hauekin sare semantiko elebakarra eraiki daitekeela erakutsi du Fontenelle-ek (1997). Lan gehienek, halere, itzulpen automatikorako lexikoen eraikuntzan laguntzeko erabili izan dituzte (Byrd, 1990; Helmreich et al, 1993; Knight & Luk, 1994; Klavans & Tzoukermann, 1995). Beste erabilera sofistikatuago batean, berriz, itzulpenaren aukeraketa automatikorako ere erabili izan dira (Rizk, 1989; Michiels, 1996).

Iturri eleanitzen arteko loturari dagokionez, ordea, lan gutxi dago. Helmreich-ek eta (1993) gaztelerazko hitzak LDOCE, WordNet eta PENMAN Upper Model baliabideak integratzen dituen PANGLOSS ontologiako kontzeptuei lotu nahi dizkiete, baina eskuz egin beharrean aurkitzen dira, nahiz eta automatizatzeko bidea aurreikusi. Bide hori Knight eta Luk-ek (1994) jorratuko dute, Collins-eko gaztelera-ingelesa hiztegiaz baliatu eta gaztelerako hitzak PANGLOSS-eko kontzeptuei lotzen dizkiete eta. Horretarako hiru heuristiko erabiltzen dituzte:

- Itzulpenean bi hitz edo gehiago badaude, eta hitz horiek WordNet-en sinonimoak edo guraso beraren semeak badira, lotu kontzeptu horiei.
- Itzulpen bakarra izanda, itzulpen hori monosemikoa bada, lotu kontzeptu horri.
- Itzulpena bakarra izanda, polisemikoa bada, erabili elebiduneko eta LDOCE-ko kode semantikoen arteko ezkontza adiera bat aukeratzeko.

Emaitzen aldetik ez dute asko esaten, ebaluaziorik ez baitute egin, baina 50.000 lotura proposatzen ditu beraien sistemak.

Garai berean antzeko ahalegin bat egiten dute Okumura eta Hovy-k (1994), kasu honetan japoniera-ingeles hiztegi bat erabiliaz ontologia berera lotzeko. Lehenbizi lotura posibleak lau multzotan sailkatzen dituzte, hitz-kontzeptu arteko erlazio posibleen arabera: hitz 1 kontzeptu 1, hitz 1 N kontzeptu, N hitz kontzeptu 1, N hitz M kontzeptu. Lehenengo eta hirugarren kasuan loturak besterik gabe egiten dituzte. Bigarren eta laugarren kasurako goiko heuristikoez gain aditzen kasuan azpikategorizazio eta argumentuen arteko ezkontza ere erabiltzen dute. Ebaluazioa nahiko iluna da, %100eko doitasuna adierazten baitute loturen %27rako, baina ez dute ematen besteetarako daturik, ez eta doitasun altuko kasuak automatikoki bereiz litezkeen edo ez azaldu ere. 15.000 hitzentzat aplikatzen dute algoritmoa.

Tesi-lan honen egilearekin batera argitaratutako artikulu batean (Rigau & Agirre, 1995), Rigauk ere bikoteen erabilera planteatzen du gaztelerako hitzak WordNet-era lotzeko, eta konbinazio posible bakoitzarentzat doitasun-neurriak hartzen ditu, frogatuaz bikoteak erabilgarriak direla zeregin honetan. Lan hau, EuroWordNet proiektuaren barruan (Vossen, 1996; Vossen et al. 1997), zabaldu egingo da (Atserias et al., 1997), tesi-lan honetan aurkezten diren tekniken antzekoak gehituaz eta, ondoren, IV. kapituluan azaldutakoaren antzera bozkatuaz. Laginen bitartez, %85etik gorako doitasuna lortzen duten bikoteak bilatu, eta horiek bakarrik onartzen ditu, gaztelerazko 10.000 inguru izen lotuaz WordNet-era.

Aipatu beharra dago lan guztiek hitzak lotzen dituztela beste hizkuntza bateko ontologiara. Lan honetan ordea, adiera edo kontzeptuak lotzen saiatuko gara, orain ikusiko dugun bezala.

VI.A.5. Gure hurbilpena: LPPL hiztegi ezagutza-basearen aberasketa

Hierarkiei egindako kritika LPPL-tik erauzitako sare semantikoari ere aplika dakioke. Artolak (1993), lehen aipatu bezala, definizioen analisia egin eta hiru definizio mota bereizi zituen izenentzat: sinonimoak, genus eta differentia motakoak, eta erlatore bidezkoak[70]. Ez zuen genus eta erlatore berezien analisi soila egin, definizioaren gainontzeko informazioa eskuratzen ere saiatu zen, erlazio aberatsak dituen sare semantikoa edo HEBa eraikiaz[71]. Sare semantiko honen bizkarrezurra hiperonimia/hiponimia erlazioaz osatutako hierarkiak dira, eta horiek sendotzen saiatuko gara lan honetan.

	Adiera kop.
Isolatuak	2190
Hierarkiatan	2743
Gainean	840
Tartean	86
Hostoak	1817
Guztira	4933

Neurria	Hierarkia kop.
1	2190
2-9	1008
10-24	25
25-49	6
>49	1

Sakonera	Hierarkia kop.
1	2190
2	784
3	47
4	9

22. taula: LPPL HEBko izenen adieren kokapena hierarkiatan (ezkerrean), eta hierarkien neurri eta sakonerak.

LPPL-n dauden adieretatik, HEBan oinarrizkoenak besterik ez ziren kargatu hasiera batean (Artola, 1993). Izenen kasuan, LPPL-ko 13.740 adieretatik 4.933 sartu ziren HEBan. Horien genus asko desanbiguatu gabe zeudenez, hierarkiak oso txikiak dira eta adieren ia erdia isolatuta dago, inongo hierarkiatan egon gabe (ikus 22. taulako datuak).

Hierarkia horiek trinkotu ahal izateko egin beharrekoak hiru ataletan bana daitezke:

70 Erlatore berezien artean sailkatu zituen *action* bezalako eduki semantikorik ez duten genusak ere.

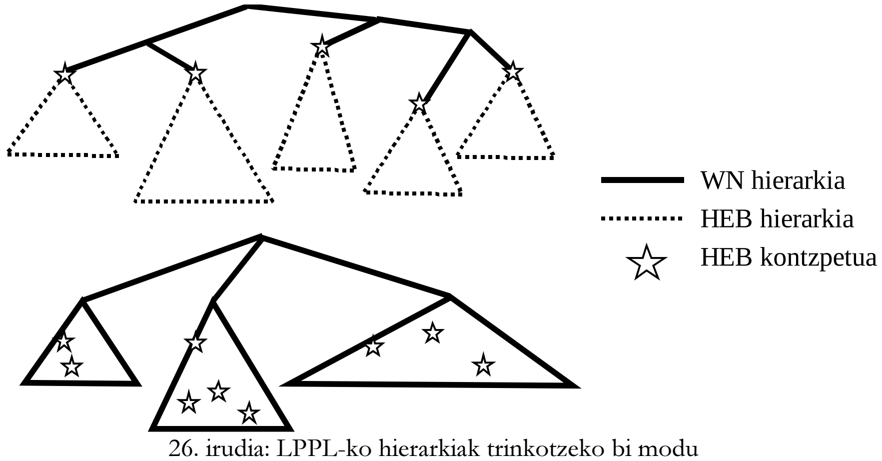
71 Hemendik aurrera HEBari buruz hitz egitean LPPL-tik erauzitako HEBari buruz arituko gara.

1. Hierarkiaren eraikuntza osatu: bigiztak askatu eta definizio erlazionalak integratu.
2. Genusen adiera-desanbiguazioa.
3. Hierarkiaren gainaren berrantolaketa.

Erabiliko ditugun bitartekoei dagokionez azpimarragarria da lehenengo aldiz LPPL-n bertan ez dagoen ezagutza sartuko dela. HEBak orain arte bestelako ezaugarria izan du: bertan dagoen informazio semantiko guztia hiztegitik bertatik erauzi izan da. HEBaren eraikuntzan egindako prozesuak inplizitu zegoena esplizitu bihurtzen saiatu ziren. Orain aldiz, hierarkiak elkarren artean erlazionatu ahal izateko kanpoko ezagutza gehitzea ezinbestekoa izango da, bai eskuz bai automatikoki.

Bestalde, genusa desanbiguatzerakoan III. kapituluan aipatutako teknikak erabili nahi baditugu baliabide egokien faltan aurkitzen gara. Badaude teknikak hiztegiko bertako ezagutza erabiltzen dutenak (ikus III.A.2 edo VI.A.2 atalak), baina gure kasuan ez dugu ez kode semantiko edo pragmatikorik eta LPPL-ko definizioak motzak dira (3,82 hitz batez-beste). Hiztegitik kanpoko baliabideetara jotzean, bestalde, HAD erabili izan dugun Dentsitatea erabili ahal izateko ontologiaren bat beharko genuke. Frantseseko ontologia zabalik existitzen ez denez, WordNet erabiltzen saiatuko gara hiztegi elebidun bat zubi bezala erabiliaz.

WordNet ontologia desanbiguaziorako oinarri bezala erabiltzeak, bestalde, beste onura bat dakar, LPPL-ko hierarkiak lotzeko eta bigizta eta erlatore bereziak integratzeko bidea izan daiteke eta. Bi aukera aurreikusi ditugu: bata, arestian azaldutako Wilks-ek eta egindako lanaren antzera (Bruce et al., 1992), WordNet-eko gaineko aldea aterki bezala erabiltzea izango litzateke, LPPL-ko hierarkien erroak lotzeko WordNet-eko goi-kontzeptu eta erlazioak hartuz. Bestea, adierak banan-bana WordNet-i lotuz gero, LPPL-ko hierarkia alde batera utzi eta guztiz WordNet-eko hierarkia gureganatzea litzateke. Hurbilpen hauek 26. irudian azaldu ditugu.

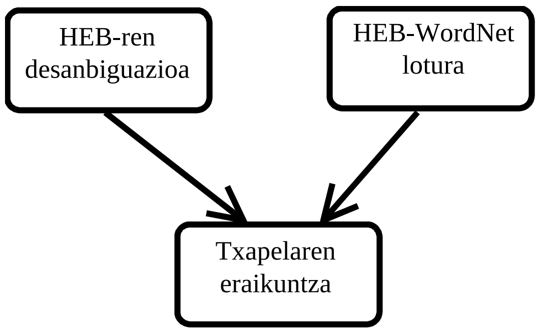


26. irudia: LPPL-ko hierarkiak trinkotzeko bi modu

LPPL-tik HEBa eratzean eduki dugun filosofiari atxikiaz (Artola, 1993), LPPL-ko egitura eta informazioa hobetsiko dugu, eta ondorioz lehenbiziko hurbilpena, *txapela kontzeptual* ere deitu duguna, aukeratu dugu. Txapela hori aurrera eramateko bi eginkizun dira beharrezkoak:

1. HEB-WordNet lotura: LPPL-ko adierak WordNet-eko kontzeptuei lotzea.
2. Txapelaren eraikuntza hierarkien gaineko adieren lotura erabiliaz.

Jadanik somatu daiteke HEBaren desanbiguazio, HEB-WordNet lotura eta txapelaren eraikuntzaren artean elkarrekintza konplexuak gertatzen direla, batak bestea egin ahal izateko informazio baliagarria eduki dezake eta. Elkarrekintza horien eragina aurrez asmatzea oso zaila denez, hipotesi sinpleenetik abiatu gara, etorkizunerako utziaz eredu elaboratuagoak. Hipotesi sinpleenean, HEB-WordNet lotura eta HEBaren desanbiguazioa independenteak dira, eta bata bestea kontuan hartu gabe eraman daitezke aurrera. Txapela eraikitzeko bai, garbi dago aurrekoen emaitzak kontuan hartu behar direla. Horrela irudikatuko dugu gure hurbilpena:



27. irudia: Prozesuen arteko dependentziak (hipotesia)

Hierarkiaren eraikuntza osatzea albo batera utzi dugu aurreko eskeman, izan ere informazioa erabili bai baina beste prozesuei ez die eskaintzen pisuzko informaziorik. Hurrengo ataletan joango gara banan-bana aztertzen eginbehar hauek.

VI.B. Hierarkiaren eraikuntza

LPPL-ren HEBan 10.506 izen daude, 13.740 adiera dituztenak. LPPL-ko hitzek duten adiera kopurua 23. taulan azaltzen zaigu. Adieren definizioen analisiaren emaitza bezala, definizioak horrela sailkatu ditugu:

- Definizio sinonimikoak
- *Genus et differentia* motako definizioak
- Definizio erlazionalak

Artolak LPPL-ko definizio guztiak automatikoki analizatu zituen (Artola, 1993; Agirre et al., 1994a). Analisi horren emaitzaren arabera gai izan gara definizioen %92, gutxi gora behera, sailkatzeko (ikus 24. taula). Sinonimo edo genusa ez denean LPPL-ko sarrera ezin izango dugu desanbiguatu, noski.

Adiera hitzeko	Izen kopurua
1	7639
2	1904
3	451
4	148
5	46
>5	18
Guztira	10.506

23. taula: LPPL-ko sarreren adiera kopurua

		%
Sinonimikoak	2836	20,6
Genus+differentia	7961	57,9
Erlazionalak	1773	12,9
Sailkatu ezinak	1085	7,9
Sinonimo/Genusa LPPL-tik at	85	0,6
Guztira	13740	100,0

24. taula: definizioen sailkapena

Definizio sinonimikoen kasuan, sinonimo bat baino gehiago erabil daitezke, eta hala da: 582 definiziotan 2 sinonimo erabiltzen dira, eta 18 definiziotan 3.

Bi arazoz arduratuko gara atal honetan, genus hierarkietan azaltzen diren bigiztak eta definizio erlazionalak hierarkian integratzeko dauden zailtasunak.

VI.B.1. Bigiztak

Genus eta sinonimoak oraindik desanbiguatu gabe daudenez, ezin da bigiztak benetakoak diren edo ez ikusi. Adibidez, nahiz eta *balle I 1*-en genusa *pelote* izan, eta *pelote I 3*-rena *balle* izan (beheko adibidean ikusten den bezala), genus horiek desanbiguatu arte ezin izango dugu jakin adieren hierarkian bigizta bat dagoen edo ez.

balle I 1 : petite pelote ronde pour joue
balle I 2 : projectile des armes à feu
balle I 3 : gros paquet
balle II 1 : enveloppe du grain des céréales

pelote I 1 : boule de fil roule
pelote I 2 : coussinet pour piquer les épingles
pelote I 3 : balle pour jouer

Bada-ezpada, definizioen artean bigizta posibleak bilatu genituen, hau da, genus eta sinonimo kateak jarraituaz gertatu zitezkeen bigiztak. Horrelako 59 balizko bigizta topatu ditugu, adibidez *balle I 1* eta *pelote I 3* artean.

Bigizta potentzialak aztertzean, konturatu gara lehenbizi desanbiguatu eta gero bigiztak bilatuz gero 59 bigizta potentzial horiek benetakoak zirela. Hipotesi hori aztertutako bigizta guztiekin betetzen zenez, bigizta-bilatzaileak bigizta horiek desanbiguatu ditu. Goiko adibidean ere, bigizta egon dadin *balle I 1*-en genusa den *pelote*, bere hirugarren adieran erabilita egon behar da, eta *pelote I 3*-ren *balle* lehenbiziko adieran. Hau da, bigizta egotekotan *balle I 1* eta *pelote I 3* artean izan beharko litzateke, eta hala da.

Behin bigiztak desanbiguatuta, arazoa apurtzea da, hau da, bigiztako zein adiera dagoen goian eta zein behean. Irizpide bezala genus bezala orokorrena aukeratzea komeni da, hori izan dadin bestearen hiperonimoa. Genus orokorragoa zein den erabakitzeko, desanbiguatu gabeko hierarkiak eginez gero azpian adiera gehien edukitzea neurtu dugu, hau da, genus bezala zenbat aldiz azaltzen den. Goiko adibidean, *balle* 5 aldiz azaltzen da LPPL-ko definizioen genus bezala, eta *pelote* behin bakarrik, eta beraz *balle* hartu dugu *pelote*-ren hiperonimo bezala. Ondoren hiperonimo bezala dagoena non kokatu erabaki beharra dago, eta horretarako WordNet-i egindako loturaz baliatuko gara, VI.C.2 eta VI.E.1 ataletan ikusiko dugun bezala.

VI.B.2. Definizio erlazionalen integrazioa hierarkian

Definizio erlazionalak mota askotakoak izan daitezke, erlazio baten bidez definitzen direnak, edo genusak eduki semantikorik eduki ez eta definizioaren funtsa differentiak daukanean (Artola, 1993). Hiztegiko beste adieraren batekin hiperonimia ez den erlazio batez lotzen direnak hierarkiatik kanpo gelditzen dira. Genus hutsa dutenak oso zailak gertatzen dira desanbiguatzen, oso izen orokorrak izaten dira eta.

Artolak egindako tratamenduaren arabera, erlatore berezi bakoitzari hiztegiko adiera bat egokitzen zitzaion eta horrela sarrera adiera horren hiponimo bezala sartzen da hierarkian. Hori eginda ere askotan ez da nahikoa, hiperonimo horiek oso orokorrak izan eta informazio gutxi ematen dute eta. Beharrezkoa zaigu beste zerbaiti lotzea, erlatore bereziaren arabera:

1. Erlatoreari hiperonimia erlazioa dagokioenean, noski, posiblea da erlazionatutako hitza genustzat hartzea, eta VI.C.2 eta VI.D ataletan ikusiko dugun bezala desanbiguatu eta WordNet-era lozea. Horrelako erlatoreak dira *espèce de, genre de* eta *sorte de*. Adibidez:
   bolet I 1 : espèce de champignon

2. Erlatoreari meronimia erlazioa dagokionean, WordNet-eko meronimia erlazioa erabil daiteke erlazionatutako hitza desanbiguatu eta WordNet-era lotzeko. Sarrera eta erlazionatutako hitzaren adieraren baten artean erlazio meronimikoa badago WordNet-en, adiera hori aukeratu

eta erabilitako WordNet-eko kontzeptuetara lotuko ditugu[72]. Erlatoreak: *membre de* eta *élément de*. Adibidez:

aristocrate I 1 : membre de l'aristocratie

3. Erlatoreari kontzeptu bat dagokionean, horri lotu hiperonimo bidez. Adibidez *qui* erlatorea erabiltzen denean sarrera pertsona dela ziurta daiteke, eta beraz *personne*-ren lehenbiziko adieraren hiponimo bezala jar daiteke sarrera hori. Adibidez:

agitateur I 1 : qui excite à la révolte

Horrelakoak dira baita ere *état de, art de, action de, faculté de, manière de, qualité de, caractère de* eta *manque de*. Erlatore hauetako gehienek kontzeptu bera adierazten dute definizio guztietan, eta beraz zuzenean esleitu daiteke adiera bakarra, *qui*-rekin egin dugun bezala. Beste erlatore batzuek, ordea, ez dute beti kontzeptu bakarra adierazten. Adibidez, *état de* erlatoreaz definitutako sarrera atributua (*état*-en lehenbiziko adiera) edo egoera (*état*-en bigarren adiera) izan daiteke. Horrelakoetan, bi aukerak irekita utzi eta 1. puntuan bezala tratatuko dira. Adibidez:

âpreté I 1 : état de ce qui est âpre

4. Erlatore batzuen kasuan, ez dira beti erabili izan erlatore bezala, hau da, batzuetan genus arruntak dira. Horren adibidea da, adibidez, *partie de* erlatorea, batzuetan meronimia adierazteko erabiltzen dena, baina salbuespen batzuetan festa bat deskribatzeko (*partie*-ren 4. adiera). Halakoak dira *partie de*, *pièce de*, *ensemble de*, *réunion de* eta *groupe de*. Bi aukerak aztertu eta fidagarritasun hoberena lortzen duena aukeratuko da. Erlazioaren aukera 2. puntuan bezala aztertuko da, eta kontzeptuaren aukera Distantzia Kontzeptualaren bidez, VI.D.6 atalean azaldu bezala.

Laburbilduz erlatoreen kasuan tratamendua honakoa izan da:

1. Erlazio hiperonimikoa denean, erlazionatutako hitza genus bezala jarri. Ondoren beste genusak bezala tratatuko dugu genus hori.
2. Erlazio meronimikoa denean, erlazionatutako hitzaren eta sarreraren artean WordNet-eko erlazio meronimikoa bilatu.

[72] Ez dugu algoritmoa gehiago zehaztuko, baina funtsean VI.C.2.b) eta VI.D.6 ataletako algoritmoen antzekoa da.

3. Erlatoreari kontzeptu bat egokitzen zaionean, zuzenean jarri hiperonimo bezala adiera hori eta WordNet-en dagokion synset-a ere (LPPL-WordNet lotura ahalbideratzeko), edo adiera bat baino gehiago daudenean sarrerarekiko Distantzia Kontzeptuala erabili..
4. Erlazio edo kontzeptu izateko aukera dagoenean, biak probatu, eta indar gehien lortzen duena aukeratu.

Behin erlatoreak modu honetan tratatu eta gero, horrela definituta zeuden 1773 definizioetatik %78 desanbiguatu eta %63 WordNet-i lotu dira. 40 adierako lagina aztertu eta bai desanbiguazioa eta bai WordNet-eko lotura %90eko doitasunarekin egin dela ikusi dugu..

VI.C. HEB-WordNet lotura: iturri lexikal eleanitzen arteko lotura

Ezagutza-baseen artean zubiak ezartzea erabilgarri suertatzen da oso. LNP orokorrerako sistema batek behar duen ezagutza ez da normalean iturri bakarrean egoten, horretarako espreski eskuz sortutako ezagutza-base bat egin ez bada behintzat. Halakoetan ere beti da aberasgarria beste ezagutza-iturrietarako zubiak sortzea. Aurrerago aipatu dugun bezala HEBko adierak WordNet-eko kontzeptuetara lotu nahi ditugu.

Hizkuntza ezberdinetako hitzez ari gara, edo hobeto esanda hizkuntza ezberdinetako kontzeptuez. Hitzak hiztegi elebidunen bidez daude lotuta, beraz frantses-ingeles hiztegia erabiliko dugu. Baina aurrerago esan bezala hitzak ez dira nahiko, beraien adieren arteko loturak interesatzen zaizkigu eta. Azken finean interesatzen zaiguna HEBko frantses hitzen adierak WordNet-eko ingeles hitzen adierei lotzea.

Modu ezberdinetara egin daiteke hau guztia:

1. lehenbizi hiztegi elebidun eta WordNet-en artean loturak ezarri eta horren emaitza erabili HEB-WordNet lotura gauzatzeko. Kasu honetan elebidun "aberastu" bat –informazio gehigarria duena– erabiliaz gauzatuko litzateke
2. zuzenean HEB-WordNet zubiak eraiki elebidun "gordina" medio.

Aukera onena zein izango den ezin aurretik esan, eta beraz banan-bana aztertu dugu bakoitza. Lehenengo bidea jorratuz gero, HEB-WordNet loturaz gain hiztegi elebidun "aberastu" bat lor dezakegu.

VI.C.1. Elebiduna-WordNet lotura

Atal honetan frantsesezko hitzak WordNet-eko adierei lotzen saiatuko gara, ahal denean WordNet-eko kontzeptu bakarrari.

VI.C.1.a) Hiztegi elebiduna

Frantses-ingeles hiztegiak –*Oxford French-English Dictionary* edo OFED (OUP, 1989), ikus II. kapitulua– 21.322 sarrera dauzka. Sarrera bakoitzak jatorrizko hitzarentzat adiera bakarra edo gehiago eduki ditzake. Elebiduneko adiera bakoitzari azpisarrera deituko diogu atal honetan. Adibidez *maintien* izenaren sarrera bi azpisarreratan bana daiteke:

maintien n.m. (attitude) bearing; (conservation) maintenance

maintien 1: n.m. (attitude) bearing
maintien 2: n.m. (conservation) maintenance

Hiztegi elebidunak 31.502 halako azpisarrera dauzka, horietako 16.917 izenei dagozkielarik. Lan honetan, esan bezala, izenetan zentratuko gara.

Azpisarreren barruan hainbat eremu azal daitezke: kategoria (derrigorrez), eremu semantikoa (aukerakoa, 20 eremutako bat izan daiteke, adibidez beheragoko adibideko *comm.*, komertziala), frantsesez dagoen argibidea (aukerakoa, adibidez goiko *attitude* eta *conservation*, edo beheko *ressources*), eta azkenik derrigorrezkoa den ingelesezko itzulpen-hitza edo hitz-zerrenda. Eremu semantikoa eta frantsesezko argibidea azpisarrera horretako itzulpena ulertzeko laguntza dira, testuinguru edo erabilpenari buruzko oharrak, hiztegiaren erabiltzaileari itzulpena hautatzean laguntzeko.

folie 1: n.f. madness
provision 1: n.f. supply, store
trésor 2: n.m (ressources) (comm.) finances

Itzulpeneko ingelesezko hitzak anbiguoak izan daitezke, WordNet-en adiera bat baino gehiago izan dezakete eta. Frantsesezko sarreraren elebiduneko adierei, azpisarrerei, dagozkien WordNet-eko adierak zeintzuk diren jakin ahal izateko, desanbiguatzeko, algoritmoak (hiztegiaren erabiltzaileak bezala) testuinguruko informazioa behar du. Ez badugu testuinguruko inongo informaziorik, eta itzulpena anbiguoa bada, orduan ez da posible WordNet-eko adiera egokia topatzea. Itzulpena desanbiguatzen saia gaitezkeen kasuak honako hauek dira:

1. itzulpeneko hitzak adiera bakarra du WordNet-en
2. itzulpena hitz-zerrenda batez ematen da

3. itzulpena frantsesezko argibide batez lagunduta dator
4. itzulpena eremu semantiko batez lagunduta dator

Aurreko atalean azaltzen diren adibideen kasuan, *folie*-ren itzulpena polisemikoa da WordNet-en, eta beraz ezin da desanbiguatu; *provision*-ek bi itzulpen dauzka, eta beraz batabestearen testuinguru izan daitezke (2. kasua); *trésor*-ek itzulpen monosemikoa dauka, eta gainera frantsesezko argibide eta eremu semantikoaz lagunduta dator (1., 2. eta 3. kasua).

Hiztegi elebiduneko izenen azpisarrerak goiko kasuen arabera sailkatu ditugu. 25. taulan azaltzen den bezala, izenen azpisarreren %52rentzat ez dugu zer eginik, itzulpena WordNet-en ez dagoelako –%24– edo itzulpen bakarra eduki eta adiera anitz dituelako –%28–. Honen arrazoiak beheragо aztertuko ditugu. 26. taulan trata daitekeen %48aren sailkapena egin dugu, kasuen arabera. Azpisarrera batzuk aldi berean egon daitezke kasu batean baino gehiagotan sailkatuta.

Itzulpena ez dago WordNet-en	4.081	%24
Itzulpen bakarra, adiera anitz	4.761	%28
1., 2., 3. edo 4. kasuak	8.075	%48
Guztira	16.917	%100

25. taula: izenen azpisarreren sailkapena (1)

1. kasua: adiera bakarra	5.039	%30
2. kasua: itzulpen anitz	630	%4
3. kasua: argibidea	2.954	%17
4. kasua: eremu semantikoa	1.067	%6

26. taula: izenen azpisarreren sailkapena (2)

WordNet-ek itzulpenen %76 bakarrik estaltzea kezkagarria zen. Arazo ezberdinek sortzen dute estaldura urri hau: itzulpena pluralean egotea, itzulpena izen-sintagma bat izatea, parentesiak, etab. Aniztasun berdina somatu genuen frantsesezko argibideetan ere. Halako itzulpen eta argibideei konplexu deitu diegu, tratamendu berezitua behar dute eta. Tratamendu hori, analisi sintaktiko zabal eta sendo baten faltan, ahal izan genuen bezala egin genuen, lematizazio eta heuristikoen bitartez. Itzulpen konplexuen tratamendua ebaluatzeko 50 azpisarrerako lagina hartu eta %88tan informazio zuzena ateratzeko gai garela ikusi dugu. Ez gara hemen gehiago arituko honetaz (ikus Rigau eta Agirre (1995) xehetasun gehiagotarako). Tratamenduaren emaitzen ondoren, 27. eta 28. tauletako sailkapena gelditzen zaigu.

Itzulpena ez dago WordNet-en	891	%5
Itzulpen bakarra, adiera anitz	6.440	%38
1., 2., 3. edo 4. Kasuak	9.586	%57
Guztira	16.917	%100

27. taula: izenen azpisarreren sailkapena (1')

1. kasua: adiera bakarra	5.119	%30
2. kasua: itzulpen anitz	958	%6
3. kasua: argibidea	3.702	%22
4. kasua: eremu semantikoa	1.365	%8

28. taula: izenen azpisarreren sailkapena (2')

Beraz, WordNet-en ez dauden itzulpenen kopurua %5era jaitsi da, eta trata ditzakegun azpisarreren kopurua %57ra igo. Horietatik 5.119k itzulpen monosemikoa dute, eta beraz 4.467 –%27–

azpisarreratan testuingurua erabili beharko dugula itzulpena desanbiguatzeko (2., 3. edo 4. kasuetan daudenak, kontuan izan azpisarrera bat kasu batean baino gehiagotan egon daitekeela).

VI.C.1.b) Emaitzak

Ideia sinplea da, HADan bezala, testuinguruari hobeto dagokion itzulpenaren adiera aukeratzea Dentsitate Kontzeptuala[73] erabiliaz. Hiztegi elebidunen kasuan testuingurua urria da, baina itzulpenarekin erlazio estuagoa izan ohi duena. Hiru testuinguru motetatik, ez dago oso garbi nola erabili eremu semantikoa, Dentsitate Kontzeptualak erlazio paradigmatikoez soilik baliatzen da eta. Horregatik oraingoz alde batera utzi dugu.

Frantsesezko argibidea duten hitzen kasuetan, argibidean azaltzen diren hitzak hiztegi elebidunean bertan begiratu eta horien ingelesezko ordainak dira testuinguru bezala erabiltzen direnak. Argibide hauek erabiliaz espero daitekeen desanbiguazioaren doitasuna kalkulatzeko esperimentu txiki bat egin genuen ia 60 azpisarrera erabiliaz. 29. taulan azaltzen den bezala, Dentsitatea erabiliaz %67ko doitasuna lortzen da. Doitasun kaxkar honen arrazoia argibideen ahultasunean bertan egon daiteke. Pista konplexuen tratamenduak eta hiztegi elebiduna erabili beharrak ere ez du laguntzen. Doitasun hori jasotzeko azterketa egin eta proba batzuk egin ondoren ikusi genuen 5 adiera baino gehiagokoak baztertuz gero doitasuna %83,3ra igotzen zela, estalduraren kaltetan.

	Estaldura %	Doitasuna %
zorizkoa	100	44,8
Dentsitatea	72,9	67,4
<6 adiera	50,8	83,3

29. taula: frantsesezko argibideetarako estimazioa

Itzulpen anitz daudenean, bakoitzak besteen testuinguru-papera joka dezake. Dentsitatea aplikatzean itzulpen guztiak batera desanbiguatzen dira. Espero daitekeen doitasuna estimatzeko halako 30 azpisarrera hartu genituen, eta 30. taulan azaltzen den bezala, doitasun eta estaldura oso onak lortzen dira. Oraingoan 5 adiera baino gehiagokoak baztertzen dituen heuristikoak ez du doitasuna apenas altxatzen.

	Estaldura %	Doitasuna %
zorizkoa	100	44,8
Dentsitatea	93,3	89,3
<6 adiera	73,3	90,9

30. taula: itzulpen anitzetarako estimazioa

[73] IV. kapituluko 20. ekuazioa, α=0,2 izanda, μ_{WN} eta erlazio meronimimoak erabiliaz.

Kasu bakoitzerako estimazioak egin ondoren, desanbiguatzeko algoritmoa izenen azpisarrera guztietarako egikaritu genuen. Eremu semantikoa alde batera utzi dugunez, 1., 2. eta 3. kasuetako azpisarrerak bakarrik desanbiguatu ahal izango ditugu. Azpisarrera bakoitza algoritmoak kasuz kasu aztertzen du: itzulpenak adiera bakarra badauka hori aukeratuko da, itzulpen anitz baditu Dentsitatea soilik erabiliko da, eta bestela, frantsesezko argibideak baditu, Dentsitatea eta heuristikoa erabiliko dira. Algoritmoa egikaritu ondoren azpisarrera guztien %43a lotzea lortu zen (ikus 31. taula).

	Azpisarrera kopurua		Doitasuna
Loturarik ez	9.676	%57	-
Lotura	7.241	%43	%95
1. kasua: adiera 1	5.119	%30	%99
2. kasua: itzulpen anitz	723	%4	%89
3. kasua: frantsesezko argibideak	1.399	%9	%83
Guztira	16.917		

31. taula: Elebidun-WN, lotutako azpisarrerak

Lotutako azpisarrera gehienak adiera bakarrari esker egin izan dira. Adiera bakarrekoetan, itzulpena konplexua denean %88ko doitasuna espero daiteke, eta bestela %100ekoa. Itzulpen konplexudunak 80 besterik ez direnez (ikus 26. eta 28. taulen arteko aldea), batez-beste adiera bakarrekoen doitasuna %99,8 da. Itzulpen anitz ditugunean %89koa eta frantsesezko argibideak dauzkatenentzat %83koa direnez, egindako 7.241 loturentzat batezbesteko doitasuna %95ekoa da.

VI.C.2. HEB-WordNet lotura

Atal honetan LPPL hiztegiko adierak WordNet-eko adieretara lotzen saiatuko gara. Horretarako erabiliko ditugun ezagutza-iturriak honakoak dira:

1. LPPL-ko adieraren definizioko hitzak, bereziki genusa eta sinonimoa[74].
2. Hiztegi elebiduna: bai bere horretan edo aurreko atalean WordNet-i lotu diogun bertsioan. Hiztegi elebiduna izango da LPPL-ko hitz frantses eta WordNet-eko ingelesezko adieren arteko zubia.
3. WordNet-eko adieren arteko Dentsitate Kontzeptuala

Hurbilpenaren filosofiaren atzean LPPL-ko genusen adiera-desanbiguazioan erabilgarria izatea dago. Horretarako komeni zaigu ahal den bezainbeste adiera WordNet-i lotuta edukitzea, baita definizio bakoitzean azaltzen den genusa lotzea ere. Estaldura ahal den zabalena eta errore ahal den

[74] Atal honetan, bai eta VI.D atalean ere, genusei buruz arituko gara, genus edo sinonimo bidezko definizioa den arduratu gabe. Izan ere genus eta sinonimo bidezko definizioak berdin tratatu ditugu.

txikiena nahi dugunez, ez zaigu arduratuko adiera bati WordNet-eko adiera anitz lotzen badizkiogu, betiere adiera zuzena horien artean badago.

Lotura egiteko algoritmo ezberdinak erabil daitezke, eta horietako batzuk ikertu ditugu. Hemen emaitza nabarmenenak azalduko ditugu. Hasteko, Dentsitatea erabili gabe, heuristiko pare baten eraginkortasuna probatuko dugu. Ondoren hiztegi elebiduna eta Dentsitatea erabiliz saiatuko gara, hiztegi elebidun hutsarekin lehenbizi, eta WordNet-i lotutako elebidunarekin gero. Bukatzeko hiztegi guztiari konbinazio hoberena aplikatuko diogu. Algoritmo horiek aztertu aurretik laginari buruz jardungo gara.

Algoritmo bakoitzaren eraginkortasuna neurtzeko 27 adierako lagina erabili dugu. 27 adiera horien definizioetan 31 genus eta sinonimo azaltzen dira. Lagina zabalagoa zen, baina genus gabekoak eta elebidunean aurkitzen ez zirenak alde batera utzi ditugu. Hiztegi elebidunak daukan beste arazo bat adieraren esanahiari dagokion itzulpena azaltzen ez denean gertatzen da. Ezinezkoa da automatikoki igartzea hori gertatzen ari dela. Eskuz, lagineko 7 kasutan gertatzen dela ikusi dugu. Algoritmoen emaitzak bi eratara emango ditugu, elebiduneko zulo horiek kontuan hartuta eta kontuan hartu gabe. Bestalde, inplementazio-arrazoiak medio, definizio baten genus edo sinonimo bat baino gehiago daudenean bakoitza aparte lotzen da, nahiz eta gero desanbiguatzerakoan informazio hori kontuan izan. Horregatik 31 genusentzat ematen dira emaitzak. Definiendum batek, beraz, bi lotura jaso ditzake, genus bakoitzetik bat.

VI.C.2.a) Hiperonimia eta beste heuristikoak

Dentsitate Kontzeptualaz gain, hiru heuristiko ere probatu ditugu. Lehenbizikoan, definiendumak hiztegi elebidunean ordain bakarra badu, eta ordain horrek WordNet-en adiera bakarra baldin badu, orduan zuzenean lot dakioke WordNet-eko adiera hori definiendumari. Heuristiko hau algoritmo guztietan erabili da.

Bigarren heuristikoari dagokionez, definiendum eta genusen itzulpenak aztertzean, batzuetan ingelesezko hitz bera bietan azaltzen zela ohartu ginen. Halakoetan, hitz hori desanbiguatu ahal izateko testuingururik azaltzen ez zenez, ingelesezko hitz horren adiera guztiak esleitzen genizkien definiendum eta genusari. Azpian ikus daitekeen bezala, adibidez, *partie*-ren 4. adieraren genusa *jeu* da, eta bai *partie* eta bai *jeu game* bezala itzul daitezke ingelesera. Hori horrela izanda *game*-ek WordNet-en dituen adiera guztiak esleituko zaizkio *partie I 4* adierari, eta gainera jakingo dugu *partie*-ren elebiduneko 2. adiera eta *jeu*-ren elebiduneko 1. adiera erabili direla definizio horretan.

partie I 4 : jeu , divertissement en commun

partie 1: part
partie 2: (cartes, sport) game
partie 3: (jurid.) party

jeu 1: game
jeu 2: (amusement) play
jeu 3: (au casino etc.) gambling
jeu 4: (théâtre) acting
jeu 5: (série) set
jeu 6: (de lumière, ressort) play

	Estaldura	Doitasuna
Itzulpen komuna	%16	%100

Bestalde, genusa definiendumaren hiperonimoa denez frantsesez, beraien itzulpenentzat WordNet-en gauza bera gertatzen den edo ez azter daiteke. Horrela, genusaren itzulpenetako baten adieraren bat definiendumaren ordezko baten hiperonimoa bada WordNet-en, adiera horiek esleituko dizkiegu frantseseko definiendum eta genusari.

	Estaldura	Doitasuna
Hiperonimia	%42	%85

VI.C.2.b) Dentsitate Kontzeptuala hiztegi elebiduna erabiliaz

Hiztegi elebidun gordina erabiliaz, posible da definiendum, genus eta definizioko gainontzeko hitzen ordainak lortzea. Definiendumari dagokion WordNet-eko adiera desanbiguatzeko Dentsitate Kontzeptuala erabili dugu, testuinguru bezala definizioko hitzen ordainak erabiliaz. Definizioko hitzen artean genusak garrantzi gehiago duenez erlazio paradigmatikoari dagokionez, Dentsitatea kalkulatzeko orduan nabaritasun-pisu (*nb*) bat esleituko diegu definizioko itzulpenen adierei: genusaren edo definiendumaren adierak badira *nb*=1, eta definizioko beste hitzenak badira *nb*=0,1 (ikus 21. ekuazioa, non *A*-n definiendum, genus eta definizioko gainontzeko hitzen itzulpenen WordNet-eko adierak dauden, eta *Z* WordNet-eko edozein zuhaitz, eta ikus IV. kapituluko 20. ekuazioa ere). Hainbat proba egin ondoren emaitza hoberenak pisu horientzat lortu ziren.

$$\text{dentsitate}(Z,A) = \text{dentsitate}(Z,a_Z) \quad \text{non } a_Z = \sum_{c\in A\cap Z} nb_c \tag{21}$$

	Estaldura	Doitasuna
Dentsitatea	%87	%74

Definizioko hitzek testuinguru gutxi eskaintzen dutenez (LPPL-ko izenen definizioek batez-beste 3,82 hitz dauzkate), testuinguru hori zabaltzea pentsatu dugu. LPPL-n hitzak erlazionatuta daude: bata bestearen genus bezala, bata bestearen sinonimo bezala, erlatore berezi baten bidez lotuta edo definizio berdinean azaltzen direla eta. Definiendum-ari WordNet-eko zein adiera dagokion erabaki ahal izateko, genusarekin erlazionatutako hitz horiek pista eman dezakete, nahiz eta ez jakin genusaren zein adiera den benetan definiendumari lotua dagoena. Alderantziz ere, genusari dagokion WordNet-eko adiera zein den erabakitzean ere, definiendumarekin erlazionatutako hitzek laguntza eskain dezakete. Testuinguru hori guztia erabiltzeko orduan aukera bat baino gehiago genituen, eta esperimentu batzuen ondoren onena Dentsitatea birritan kalkulatzea zela ikusi genuen: genusa desanbiguatzeko definiendumaren testuingurua erabili eta definienduma desanbiguatzeko genusaren testuingurua erabili, bietan definizioko gainontzeko hitzak ere erabiliaz. Lehen bezala nabaritasun-pisua erabili dugu: *nb*=1 testuinguruko genus edo sinonimo bezala erlazionatutako hitzei, eta nb=0,1 erlatore bidez edo definizioan egoteagatik erlazionatutako hitzei.

	Estaldura	Doitasuna
Dentsitatea (erlazioekin)	%97	%63

Doitasuna erlazionatutako hitzak erabili gabe baino okerragoa da, baina estaldura %100era hurbiltzen da. Orain lehen baino datu gehiago dauzkagu, baina sistemak ez ditu guztiz aprobetxatzen. Hurrengo atalean (ikus VI.D) azalduko dugun bezala, estaldura garrantzitsua izango da LPPL-ren genus desanbiguazioa aurrera eramateko, eta horren alde egin genuen aukera. Teknika honen emaitzak hobetzen saiatuko gara hurrengo ataletan.

VI.C.2.c) Dentsitate Kontzeptuala elebiduna-WordNet lotura erabiliaz

Atal honetan hiztegi elebidun landu gabea erabili ordez, aurreko atalean WordNet-ekin lotura duen bertsioaz profitatzen saiatu gara. Aurreko atalean frantseseko hitz bati dagozkion WordNet-eko adierak lortzeko, lehenbizi elebidunean itzulpena lortu eta ondoren itzulpen horien adierak begiratzen genituen. Orain, ordea, elebidun landuan zuzenean atzi daitezke WordNet-eko adierak. Gogoratu bertsio honetan adiera batzuk desanbiguatuak izan direla, beste batzuk baztertuaz. Esperimentuan erlazionatutako hitzak ere erabili ditugu, eta doitasuna nabari igo da.

	Estaldura	Doitasuna
Dentsitate (erlazioekin eta elebidun aberastuarekin)	%97	%70

VI.C.2.d) Konbinazioa

Orain arte aipatutako heuristikoak eta Dentsitatea, ordena jakin batean egikaritzea erabaki dugu:

1. Itzulpen bakarra eta adiera bakarrekoa badu definiendumak, lotu horrekin.

2. Bestela, definiendum eta genusak itzulpen bera badute, horren WordNet-eko adiera guztiekin lotu.
3. Bestela lotura hiperonimikoak erabili.
4. Bestela erabili Dentsitatea VI.C.2.c) atalean bezala.

	Estaldura	Doitasuna
Konbinazioa	%97	%77

Bestalde, bai elebidun eta bai WordNet begiratzean sortzen ziren arazo batzuk ere tratatu izan dira: lematizazioa, frantseseko hiztegiko sarrera konplexuak, etab. Arazo horiek ebazten saiatu ondoren doitasuna are gehiago igotzen da, eta estaldura %100era heltzen da. Emaitzak aztertzean konturatu gara LPPL-ko adiera batzuk ez daudela elebidunean, hau da, frantses hitzen adiera guztiak ez daudela behar den bezala itzulita elebidunean. Halako adiera bat lotzean emaitza okerra lortu dugu ziurrenik. Laginean behar bezala itzulita dauden adierak uzten baditugu soilik –31 definizioetatik 24– doitasuna %88ra igotzen da.

	Estaldura	Doitasuna
Konbinazioa + tratamendua	%100	%82
" + itzulpen zuzenekoak soilik	%100	%88

Laginerako emaitzak ikusita, azkeneko algoritmo hau LPPL hiztegi osoarekin egikaritu genuen. Estaldurari buruzko datuak, eta loturaren iturriari buruzko datuak 32. taulan azaltzen dira. Aipatu beharra dago laginean estaldura %100 zenean, hiztegi guztirako %64,8 dela. Laginean definizio erlazionalak, genus gabekoak eta hiztegi elebidunean topatu ezin zirenak alde batera utzi genituen, baina hiztegi osoa tratatzean, horrelakoak (adieren %35,1) ezin WordNet-era lotu, noski.

Adiera kopurua	13740	
Loturarik ez	4832	%35,1
Definizio erlazionalak	1462	%10,5
Genusik ez	1085	%7,9
Elebidunak kale	2285	%16,6
Lotura	8908	%64,8
Lotura bakarra	4976	%36,2
Elebiduneko adiera bakarra	1828	%13,3
Elebiduneko adiera anitz	2104	%15,3

32. taula: LPPL-WN emaitza orokorrak

Definizio erlazionaletako batzuek –280– lotura lortu dute, adiera bakarreko itzulpena zuten eta. Kasu gehienetan bai definienduma eta bai genusa lotu dira, baina lotutako adieren %6,21ean definiendumak ez du loturarik eta %18,48an genusa da loturarik ez duena. Loturen jatorriari buruzko datuak 33. taulan daude jasota.

1. adiera bakarra 2. sinonimia	%7,18
3. hiperonimia	%42,37
4. Dentsitatea	%50,45

33. taula: loturen jatorria

VI.C.2.e) Nabarmentasunean oinarritutako hedadura

Goiko metodoen konbinazioarekin, hiztegiko izenen %64 WordNet-eko adierei lotzeko gauza gara. IV.C.3.a) atalean aipatu dugun bezala, WordNet-eko adiera jakinda WordNet-eko etiketa semantikoa ere ezagut dezakegu. Etiketa semantiko horiek oso interesgarriak dira, adiera baten eremu semantikoa adierazten digute eta (ikus II. kapitulua). Gainera, oraindik lotu gabe dagoen hiztegiko adiera baten etiketa semantikoa jakinez gero, errazagoa da hari dagokion WordNet-eko adiera (bat edo gehiago) lortzea. Adibidez, orain ikusiko dugun teknikaren bidez, posiblea da *adulte I 1* adierari *noun.person* etiketa semantikoa esleitzea (ikusi behean), pertsonei buruzko definizioa delakoan. *Adulte*-k itzulpen bakarra du, *adult*, eta honek bi adiera ditu WordNet-en, pertsonei buruzkoa bata eta animaliei buruzkoa bestea, eta horrela *adulte I 1* adierari WordNet-eko *adult/1* adiera dagokiola ondorioztatu ahal izango dugu.

adulte I 1 : arrivé à l'âge d'homme ⇒ noun.person

adulte: adult

adult 1: <noun.person> adult, grownup: a fully developed person from maturity onward
adult 2: <noun.animal> adult: any mature animal

Orain arte lotutako adierei esker, etiketa semantiko jakin bati dagozkion frantseseko adierak eta definizioak bil ditzakegu, etiketa semantiko bakoitzarekin erlazionatutako hitz multzoa lortuz. Behin hitz multzo horiek bilduta Yarowsky-ren (1992) teknika erabil dezakegu etiketa semantiko bakoitzaren hitz nabarmenenak ezagutzeko, eta hitz nabarmen horiek erabilita oraindik lotu gabe dauden definizioak etiketatzeko (ikus III.A.4 atala).

Goian aipatutako prozesu horri esker aurreko atalean lotu gabe gelditu diren definizioak lotzeko gai izan gaitezke. Metodo honen doitasuna estimatu ahal izateko lagin bat hartu dugu, etiketatu gabeko 40 adieraz osatua, eta %70eko doitasuna neurtu dugu. Nabarmentasun neurri handiagoa zuten kasuetan emaitza hobeagoak lortzen diren edo ez neurtu nahi genuen. Nabarmentasunaren balio minimo bat exigituz gero, doitasuna hobetzea lortzen da estalduraren kaltetan (ikus 34. taula).

Nabarmentasun minimoa	doitasuna	estaldura
0	%70	%100
1	%78	%88
2	%81	%65

34. taula: nabarmentasunaren bidezko hedadura (lagina)

Hiztegi osora aplikatzean estaldura ez da hala ere %100era heltzen. Definizio batean, gerta daiteke hitzetako bat ere ez egotea etiketa semantiko baten nabarmentasun-zerrendetan. Horrela denean ez dago adiera horri etiketa semantikoa esleitzeko oinarririk. WordNet-eko adierak esleitzeari dagokionez, definiendum edo genuserako elebidunaren bidez topatutako WordNet-eko adiera guztietatik, etiketa semantikoa betetzen dutenak bakarrik aukeratuko dira. Elebidunean dagoen estaldura eskasa dela eta, nahiz eta etiketa semantikoa eduki, ezin izan dira beti definiendum eta genusak WordNet-eko adierei lotu, baina bai bata edo bestea.

VI.C.2.f) Emaitzak

Behin nabarmentasunaren bidezko loturak eta erlatore berezien bidezkoak gehitu ondoren, hiztegiko adieren %87 lotzea lortu dugu, 35. taulan azaltzen den bezala. Aurreko ataletan azaldutako lagin ezberdinetarako emaitzak kontuan izanda, erlatore bidezko loturentzat %90eko doitasuna espero dezakegu, Dentsitate bidez lortutakoentzat %82, eta nabarmentasuna erabiltzen dutenetarako %70. Hiru neurrien batezbestekoa eginez gero WordNet-en loturentzat espero daitekeen doitasuna %80koa da.

WN-era lotu gabe	1824	%13
WN-era lotuta	11916	%87
Erlatore	1114	%8
Dentsitate	8615	%62
Nabarmentasun	2187	%16
Guztira	13740	

35. taula: LPPL-WN loturaren emaitzak

VI.C.3. Ebaluazioa

Hiztegi elebiduneko hitzak WordNet-eko adierekin lotzean lortu zen estaldura nahiko apala da (%43), nahiz eta doitasun altua lortu (%95). Estaldura zabalagoa lortzeko hiztegi elebiduneko eremu semantikoak erabiltzeko sistema bat pentsatu beharko litzateke. Bestalde bikoteen azterketa egin zitekeen, doitasun apalagoa edukita ere lotura asko egitea posible egiten baitu (Okumura & Hovy, 1994 ; Rigau & Agirre, 1995; Atserias et al. 1997). Guk erabilitako hiztegi elebiduna aberatsagoa eta zabalagoa izango balitz ere (aipatutako lanetan erabilitakoen antzera) lotura gehiago lortuko genituzke, bai frantsesezko hitz gehiago egongo liratekeelako, baita itzulpen anitzen bidez desanbiguatzeko aukera gehiago egongo liratekeelako ere.

Elebidun zabalagoarekin HEB-WordNet emaitzak ere hobetuko lirateke. Alde batetik estaldura zabalagoa lortuko litzateke, bai hiperonimo eta bai Dentsitatearentzat bereziki (doitasun orokorra hobetuaz), eta bestetik LPPL-ko adieraren baterako itzulpenik ez egotea errore-iturri denez, elebidun zabalagoarekin halako gutxiago gertatuko lirateke. Dentsitatearen bidez lortutako LPPL-WordNet loturetan, adibidez, doitasuna %82tik %88ra igoko litzateke, lehen aipatu dugun bezala.

Bestalde, elebiduna-WordNet lotura erabiliaz, nahiz eta elebidunaren %43 besterik ez eduki lotuta, Dentsitatearen doitasuna %63tik %70era igotzen da. Beraz, merezi du lehenbizi elebiduna lotzea eta lotura hori erabiltzea HEBa lotzeko. Elebiduna-WordNet loturan lehen aipatutako bikoteak erabiliz gero, HEB-WordNet loturan ere emaitza hobeak lortuko liratekeela espero dugu. Dena den, esandako lanetan bikoteak hizkuntza bateko hitzen eta ingelesezko ontologiaren arteko loturak egiteko erabili dira, ez adiera edo kontzeptuen eta ingelesezko ontologiaren artean, guk nahi dugun bezala.

Bikoteen erabilerari buruz aipatu behar da (Atserias et al, 1997) lanean elebiduneko adierak ez direla kontuan hartzen, Okumura eta Hovy-renean ez bezala (1994). Elebiduneko adierak kontuan hartzeak elebiduneko argibideak eta itzulpen anitzak erabiltzea ahalbideratzen du. Bestalde, elebidunean dagoen informazioa (kolokazio, kode semantiko, frantsesezko argibidea, etab. (Fontenelle, 1997)) WordNet bera aberasteko erabil daiteke, eta HEB-WordNet lotura egitean, itzulpenerako erabili den elebiduneko adiera zein izan den gordetzen denez, LPPL-ko adierak ere aberats daitezke. Lotura honen inplikazio guztiak ez ditugu sakonean aztertu. HEB-WordNet lotura medio, noski, batek duen informazioa erabiliz bestea aberats daiteke, VI.E atalean ikusiko dugun bezala..

VI.D. HEBko kontzeptuen desanbiguatze lexikala

Atal honetan LPPL-ko definizioetan azaltzen diren genus, sinonimo eta erlatore berezien bidez lotutako hitzen desanbiguazioari buruz arituko gara. Erlatore bereziek jaso duten tratamendua aipatu izan dugu jadanik VI.B.2 atalean, baina erlatore batzuek hiperonimo erlazioa islatzen zutenez, horientzat genusaren papera jokatzen zuen hitza topatu eta genus bezala tratatu dugu. Bestalde, genus eta sinonimoen desanbiguazioa era berdinean tratatu dugu, VI.C atalean bezala. Izan ere sinonimo asko ez dira halakoak, hiperonimoak baizik, hau da, diferentzia gabeko genusak dira. Gainera, sinonimoak izanda ere, Dentsitatearen bidezko desanbiguazioa aproposa da.

HADaren kapituluan ez bezala, orain gure helburua ez da Dentsitatearen egokitasuna frogatzea bakarrik. Beraz, Dentsitate Kontzeptualaz gain, bestelako heuristikoak ere erabiltzea erabaki dugu, heuristiko guztiak bozketa bitartez konbinatuz. Desanbiguaziorako metodoak bi multzotan bana daitezke: barne-ezagutza soilik darabiltenak eta kanpokoa ere badarabiltenak. Lehenbiziko taldean leudeke lehen adiera, agerkidetza eta bektoreetan oinarritutako teknikak, LPPL hiztegiko informazioan, definizioetan, oinarritutakoak. Bigarrenean LPPL-WordNet loturatik erauzitako etiketa semantikoez osatutako bektoreak eta Dentsitate Kontzeptuala ditugu, LPPL-ko informazioaz gain WordNet ere erabiltzen dute eta. Hurrengo ataletan banan-bana azalduko dugu teknika bakoitza, eta ondoren konbinatzeko modua eta lortutako emaitzak ikusiko ditugu.

VI.D.1. Adieren ordena (OR[75])

Heuristiko honek adierak garrantziaren arabera ordenatuta daudela suposatzen du, hau da, adiera erabilienak arraroagoak baino gehiagotan emango direla. Lehenbiziko adierari 1 esleituko dio, bigarrenari 0,9, etab.

VI.D.2. Definizioko hitzen ezkontzea (EZ)

Lesk-ek (1986) erabilitako teknika bera aplikatzen dugu hemen. Genusaren adiera bakoitzeko definizioetako hitzak definiendumaren definiziokko hitzekin[76] konparatu, eta hitz berdin[77] bakoitzeko puntuazioa gehitu egiten da. Hitz gehien amankomunean dauzkan adiera da aukeratuko lukeena, horri 1 pisua emanaz, eta besteei normalizatutako balioa.

VI.D.3. Agerkidetza arruntak (AA)

Bi hitz definizio berean gertatzen direnean agerkidetza bikotea dugula esango dugu. LPPL-tik horrelako agerkidetza bikoteak atera genituen. Agerkidetza bikote baten indarra neurri ezberdinez isla daiteke: maiztasun gordina, Elkarren Arteko Informazioa (EAI, ikus III. atala) edo *Association Ratio* (AR, Resnik, 1992) deritzana. Gure kasuan, emaitza hoberenak agerkidetza arrunten kasuan AR erabiliaz lortu ditugu.

Hitzen ezkontzarekin bezala, definiendum eta genusaren adiera bakoitzaren definizioa konparatuko ditugu hemen ere, baina ez zuzenean ea hitzak berdinak diren begiratuaz, zeharka baizik. Definizio eta genusaren adiera baten arteko erlazioaren indarra (22. ekuazioko GA(D,G_i)) neurtzeko,

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75 Teknika bakoitzari laburdura bat emango diogu, tauletan erabiltzeko.

76 Hitzak berdinak direla erabakitzeko lemak erabili ditugu, ez hitz-formak. Bestalde funtzio-hitzak (izen, adjektibo eta beste kategoria irekietakoak ez diren hitzak, adibidez *et, le,* etab.) ez dira kontuan hartu, gainontzeko tekniketan bezala.

77 $\mathrm{AR}(v,w) = \Pr(v,w)\cdot \mathrm{EAI}(v,w) = \Pr(v,w)\cdot \log \dfrac{\Pr(v,w)}{\Pr(v)\cdot\Pr(w)}$

definiendum eta genusen definizioetako hitzen arteko agerkidetzak aztertuko ditugu, beren pisuak batuaz (gp-k bi hitzen arteko agerkidetza indarra adierazten du).

$$\mathrm{GA}(D,G_i)=\sum_{w_j\in D\wedge w_k\in G_i}\mathrm{gp}(w_j,w_k) \tag{22}$$

VI.D.4. Agerkidetza bektoreak (AB)

Wilks-ek eta (1990) agerkidetza bektoreak erabiltzea proposatu zuten agerkidetza arrunten ordez. III.A.2 atalean azaldu dugun bezala, hitz batekin azaltzen den agerkidetza guztien bidez osatzen da hitzaren agerkidetza bektorea. Bai definiendum eta bai genusaren adieraren bektorea eraikitzeko beraien definizioetan dauden hitzen bektoreak batu besterik ez dago. Genusaren adieretatik definiendumaren bektoretik gertuen dagoena aukeratuko dugu, bektoreen arteko hurbiltasun-neurriren bat erabiliaz (ikusi 23. ekuazioa).

$$\mathrm{GB}(D,G_i)=hurbil(\vec{b}_D,\vec{b}_{G_i}) \tag{23}$$

Hainbat proba egin genituen hurbiltasun-funtzio ezberdinak erabiliaz (distantzia euklidearra, kosinua edo bektoreen arteko puntu-biderkaketa –*dot product*–), baita agerkidetzaren indarraren neurri ezberdinekin (maiztasun gordina, EAI eta AR) ere. Emaitza onenak EAI-z osatutako bektoreen arteko kosinuak eman zituen.

VI.D.5. Etiketa semantikoen bektoreak (SB)

Aurreko atal batean (VI.C.2) ikusi dugu nola lotu LPPL-ko definizioak WordNet-eko adiera eta etiketa semantikoei. Etiketa semantikoei dagokionez, definizio batek pisu bat lortzen du etiketa bakoitzeko (ikus VI.C.2.e). Etiketa bakoitzeko pisu horiek bektore moduan antola daitezke, eta behin bektore moduan antolatuta, aurreko atalean bezala, bektoreen arteko hurbiltasuna neurtu. Hurbiltasun neurri ezberdinak probatu ondoren, kosinuarenak eman zituen emaitza onenak.

VI.D.6. Distantzia Kontzeptuala erabiliaz (DK)

LPPL-ko definizioak WordNet-eko adierei lotu izan ditugun bezala (ikus VI.C.2.b), posiblea da hiztegi elebiduna eta WordNet erabiltzea ere definiendum eta genusaren adiera bakoitzaren arteko erlazio-izaera bilatzeko. Erlazio-izaera hori bilatzeko orduan erabili beharreko testuingurua finkatu behar da. Kasu sinpleenean, definiendum eta genusaren adierako definizioaren genusaren arteko Dentsitatea neur dezakegu.

Horretaz gain definizioetako gainontzeko hitzak ere erabiltzea badago, hala nola erlazionatutako hitzak (VI.C.2 atalean bezala). Aukera ezberdinak eta nabaritasun-pisu eskema ezberdinak ere probatu ondoren, ikusi dugu bai aukera sinpleena edo bai bitxiena hartuta ere ez dagoela hobekuntza handirik. Gainera, bi kontzepturen arteko hurbiltasun kontzeptuala neurtu behar denez soilik, Dentsitatearen ordez Distantzia Kontzeptuala (ikus III. kapituluko 13. ekuazioa) erabiltzea erabaki dugu.

VI.D.7. Heuristikoen arteko bozketa

Heuristiko guztien emaitzak konbinatzeko orduan, ikasketa automatikoan (*machine-learning*) hainbesteko arrakasta lortu duen sistema sinplea erabili dugu: bozketa. Dietterich-ek (1997) dioen bezala, "*while it may appear that more intelligent voting schemes should do better, the experience in the forecasting literature has been that simple, unweighted voting is very robust*". Beraz, heuristikoen bozketa sinplea erabili dugu, orain azalduko dugun bezala.

Aipatu dugu jadanik heuristiko bakoitzak genusaren adiera bakoitzari pisu bat esleituko diola. Pisu hori 1ekoa izango da egokien bezala jo den adierarentzat eta 0tik 1era doan balio batekoa gainontzekoentzat. Tarteko pisu hori lortzeko heuristikoen berezko balioak, 24. ekuazioko balio(D,G_i) –D definiendumaren eta G_i genusaren i-garren adieraren arteko erlazio-izaeraren neurria–, normalizatu egiten dira. Horretarako balio hori genus horren beste adierentzat lortutako balio maximoaz zatitu egiten da. 24. ekuazioan azaltzen da edozein heuristikok genusaren adiera batentzat (G_i) emandako bozaren pisua.

$$\text{pisu}(D,G_i) = \frac{\text{balio}(D,G_i)}{\max_{G_j}(\text{balio}(D,G_j))} \tag{24}$$

Boza emateko arauei dagokionez, heuristiko batzuek (adibidez Distantzia Kontzeptualak) adiera guztiei pisuren bat ematen diote, beharrezko informazioa eskura baldin badute behintzat. Adiera bati buruz heuristikoak ezin badu ezer erabaki (adibidearekin jarraituaz, hiztegi elebidunean zulo bat badago), ezin gara arriskatu beste adiera aukeratzera. Beste heuristiko batzuentzat (adibidez definizioko hitzen ezkontzea), ordea, nahiko da adiera baten ezagutza edukitzea adiera hori aukeratzeko. Beraz bitan sailkatu dira heuristikoak: agerkidetza bektoreak, etiketa semantikoen bektoreak eta Distantzia Kontzeptuala alde batetik, eta adieren ordena, definizioko hitzen ezkontzea eta agerkidetza arruntak bestetik. Lehenbiziko multzokoetan, genusaren adieraren batentzat ezin bada bozik eman, orduan ez da bozik emango genus horren gainontzeko adierentzat. Bigarren multzoko heuristikoek, ordea, beti emango dute boza.

Genusaren adiera bakoitzerako heuristiko bakoitzak ematen duen bozaren pisua batzen da, eta pisu handiena lortzen duen genusaren adiera izango da hautatua.

VI.D.8. Emaitzak

Laginaren datuak 36. taulan aurkezten ditugu. 115 genus desanbiguatzen saiatu gara. %3tan genusa bilatzen zuen programak kale egin du. Batezbesteko adiera kopurua genus bakoitzeko 2,29 da, nahiz eta %36an adiera bakarra eduki. Lagina eskuz desanbiguatu dugu aurrez, eta egokia zenean adiera bat baino gehiago ontzat eman ditugu. Batez-beste 20 genusetatik batek dauzka bi adiera onargarri.

Lagina	115
Genus zuzena topatu	111 (%97)
Genusak adiera bakarra	40 (%36)
Adierak genus bakoitzeko	2,29
” (polisemikoentzat)	3,02
Adiera zuzenak genus bakoitzeko	1,05
” (polisemikoentzat)	1,06

36. taula: laginaren datuak

Heuristiko bakoitzak eta bozketak genus polisemikoentzat lortzen dituzten emaitzak 37. taulan azaltzen dira. Lehenbiziko zutabean zorizko hautaketak[78] lortuko zituzkeen emaitzak gehitu ditugu. Heuristikoek, banan-banan hartuta, emaitza kaxkarrak lortzen dituztela dirudi, baina beti zorizko emaitzen gainetik. Doitasuna eta estaldura kontuan hartuz gero, adieraren ordenari buruzko heuristikoa da hoberena. Doitasunari dagokionean Distantzia Kontzeptuala azpimarratu beharko litzateke, onena izateagatik, eta agerkidetza arruntak, okerrena izateagatik. Harrigarria izan daiteke, sinplea den heinean, definizioko hitzen ezkontzak lortu duen doitasuna. Heuristiko gehienek adiera bakar bat aukeratzen dute normalean, Distantzia Kontzeptualak izan ezik. Honek batez-beste 1,25 adiera aukeratzen ditu. Estaldurari dagokionez, heuristiko gehienak kasu gutxitan aplikatu ahal izan dira.

	Zorizkoa	OR	EZ	AA	AB	SB	DK	Bozketa
Doitasuna	%36	%66	%66	%44	%61	%57	%76	%73
Estaldura	%100	%100	%12	%25	%36	%19	%66	%100

37. taula: genus polisemikoentzat lortutako emaitzak

Heuristikoen bozketak emaitza onenak lortzen ditu zalantzarik gabe: doitasun ia hoberena eta estaldura osoa. Nahiz eta Distantzia Kontzeptualaren doitasunarekin alderatzean iruditu 3 puntu gutxiago lortzen dituela, bozketak adiera bakarra hautatzen du, distantziak ez bezala. Bozketak,

[78] Zorizko emaitzak analitikoki kalkulatu ditugu, genus polisemikoak dituzten adiera kopuruak erabiliaz.

beraz, heuristiko guztien emaitzak gainditzen ditu. Genus monosemikoak ere kontuan hartzen baditugu bozketaren doitasuna %82ra igoko litzateke (ikus 38. taula).

	Zorizkoa	Bozketa
Doitasuna	%59	%82
Estaldura	%100	%100

38. taula: genusentzat (monosemikoak barne) lortutako emaitzak

Heuristiko guztien bozketak emaitza onenak lortuta ere, zalantzan jar daiteke heuristiko guztiak beharrezkoak direnik. Heuristiko bakoitzaren ekarpena neurtzeko bozketa errepikatu genuen, baina heuristiko bat ezabatuaz kasu bakoitzean. 39. taulan azaltzen den bezala, edozein heuristiko kenduz gero doitasuna gutxienez 4 puntu erortzen da. Gale-k eta (Gale et al., 1993) ez dute uste hitz polisemikoentzat doitasuna %75 baino gutxiagokoa duten adiera-desanbiguatzaileak kontuan hartu behar direnik. Gure emaitzak, ordea, doitasuna %44 bezain baxua duen agerkidetza arrunta erabili gabe bozketaren emaitza 6 puntu erortzen dela adierazten du (39. taulako -AA zutabea). Beraz, heuristiko kaxkarrenek ere besteek ez duten ezagutzaz laguntzen dute emaitza hobetzen. Hau ados dago Dietterich-ek (1997) esandakoekin, heuristikoen konbinazioak heuristiko isolatuak baino doiagoak izan daitezkela esaten duenean. Horretarako baldintza bakarra, Dietterich-en ustez, heuristikoak elkarrekin ados ez egotea litzateke, hau da, bata bestearekin ahal den independienteena izatea, ezagutza ezberdina erabiltzea.

	Bozketa	-OR	-EZ	-AA	-AB	-SB	-DK
Doitasuna	%82	%75	%73	%76	%77	%77	%78
Estaldura	%100	%99	%100	%100	%100	%100	%100

39. taula: heuristikoen ekarpena, genus monosemikoak barne

VI.D.9. Ebaluazioa

Bigizta eta erlatore berezien tratamendua (ikus VI.B atala) eta genus-desanbiguazioa integratuz gero, genusa daukaten LPPL-ko adieren %97 desanbiguatu dugu (adiera guztien %88, ikus 40. taula), hiperonimiaren bidez hierarkiatan antolatuaz. Taula berean azaltzen da adierak zein metodoren bidez desanbiguatu izan diren. Genusik topatu ez zaien adierak ere hierarkiatan integratu gabe gelditu dira, noski. Desanbiguatuetatik, erlatore bidez egin direnentzat doitasuna %90ekoa da, monosemikoentzat %100ekoa eta bozketa bidez egindakoentzat %73koa. Batezbeste %84ko doitasuna edukiko genuke desanbiguatutako loturentzat.

Genus gabe	1251	%9
Desanbiguatu gabe	368	%3
Desanbiguatuta	12137	%88
Erlatore	1378	%10
Genus monosemikoa	4089	%30
Genusa (bestela)	6670	%48
Guztira	13740	

40. taula: genus-desanbiguazioaren emaitza orokorrak

Hurrengo atalean hitz egingo dugu desanbiguatu ondoren lortzen diren hierarkiez, baina lehendabizi aldera dezagun beste lanekin.

Genusen desanbiguazioan egin den lan ezagunenak (Bruce et al., 1992) LDOCE hiztegian kodetuta dauden informazio semantiko eta pragmatiko bereziak erabiltzen ditu. Gainera, adierak maiztasunaren arabera ordenatuta daude, lehenbiziko adiera usuena izanez. Ingelesa ez diren hizkuntzetarako ordea, ez da ohikoa halako informazio aberatsa edukitzea hiztegian. Lan honetan aurkeztu diren teknikak guztiz orokorrak dira, eta edozein hiztegi elebakarretarako balio dute, definizioetako testua besterik ez du erabiltzen eta. Hala ere, LDOCE-rako lortutako emaitzen parekoak lortzen ditugu, nahiz eta LPPL-ko definizioak askoz laburragoak izan. LDOCE-ko kodeketa bereziak erabiltzen duen metodo automatikoaren bidez %80ko doitasuna lortzen dute, guk aldiz %84. Beraiek genus usuenak aztertu eta horientzat adiera jakin bat emanaz doitasun hori %90era jaso zuten.

VI.E. HEBaren goiko geruzaren osatzea

Aurreko ataletako informazioa erabiliaz, hierarkiak beren artean lotzen saiatuko gara orain. Lehenbizi orain arteko lanarekin eraiki daitezkeen hierarkiak aztertuko ditugu.

VI.E.1. Hierarkien eraikuntza

Genusen desanbiguaziotik lortutako adierei, erlatore bidezkoen emaitzak gehitu behar zaizkie eta bigizten tratamendua aplikatu (ikus VI.B atala). Orain arte ez bezala, sinonimoei eta genusei tratamendu ezberdina emango diegu, genusak soilik sartzen dira berez hierarkia eraikuntzan, hiperonimia erlazioa adierazten baitute. Genus edo erlatore bidezko hiperonimia erlazioak lotzen baditugu, hierarkiak osatuko ditugu. Behin hierarkiak eraiki eta gero, LPPL-ko 13.740 adieretatik 10.241 adiera integratu ditugu 710 hierarkiatan, eta 3499 adiera isolatuta gelditu dira. Horrek esan nahi du, isolatutako adierez gain, hierarkien 710 erroak ere gelditu direla hiperonimo gabe. 41. taulan azaltzen da lotu gabeko adiera horien jatorria, eta nabarmena da sinonimoak direla ugarienak.

	Erroak	Isolatuak
Genusak	39	80
Erlatoreak	46	123
Sinonimoak	504	2.331
Analisi gabe	121	965
Guztira	710	3.499

41. taula: erro eta adiera isolatuen jatorria

Sinonimo horietatik asko desanbiguatuta daude, eta nola edo hala hierarkiatan integratzea badago. Lehenbiziko hurbilpen bezala, desanbiguatuta daudenean, beren sinonimoa hierarkiaren baten barne dagoen konprobatu, eta hala bada sinonimo horren senide bezala koka daitezke, beti ere zikloak sortzen ez direla ziurtatuaz. Hala egin ondoren hierarkia batzuk fusionatu eta isolatuta zeuden adiera batzuk hierarkietara lotzen dira, 527 hierarkia eta 2.258 adiera isolatu utziz.

	Erroak	Isolatuak
Genusak	39	80
Erlatoreak	46	123
Sinonimoak	321	1.090
Analisi gabe	121	965
Guztira	527	2.258

42. taula: erro eta adiera isolatuen jatorria, sinonimo batzuek tratatu ondoren

Oraindik ere sinonimoak dira lotu gabeko gehienak. 265 adiera izan ezik, beste guztiak desanbiguatuta daude, baina halere adiera hauek zikloak sor ditzakete. Esan dugunaren adibide bat *paysage* eta *vue*-ren bi adieren artean pasatzen da, *vue paysage*-en genusa izanda bere 5. adierara desanbiguatu dugu, eta *paysage vue*-ren sinonimoa izanda bere 1. adierara, hemen ikus daitekeen bezala.

paysage I 1 : ***vue*** *d'ensemble d'un site*
vue I 5 : ***paysage***

Sinonimoentzako tratamendu sofistikatuagoa pentsatu beharko litzateke, baina oraingoz zikloak sortzen dituzten sinonimoak ez ditugu integratuko hierarkian. Lortutako hierarkien neurri eta sakoneren datuak 43. eta 44. tauletan daude.

Neurria	Hierarkia kopurua	Portzentai metatua (%)
100-3293	13	0,5
50-99	15	1,0
25-49	22	1,8
10-24	67	4,2
2-9	410	18,9
1	2258	100,0

43. taula: hierarkien adiera kopuruak

Sakonera	Hierarkia kopurua	Portzentai metatua (%)
10	1	0,0
9	1	0,1
8	2	0,1
7	4	0,3
6	5	0,5
5	24	1,3
4	50	3,1
3	110	7,1
2	330	18,9
1	2258	100,0

44. taula: hierarkien adiera kopuruak

VI.E.2. "Txapelaren" inplementazioa

Goiko geruza (txapela) horren diseinua VI.A.5 atalean aurkeztu duguna da, hierarkien erroak WordNet-eko kontzeptuei lotzea. Bestalde, adiera batzuk isolatuta gelditu dira, inongo lotura gabe, eta horiek ere lotzen ahaleginduko gara. Adiera bat hiperonimo gabe gelditzeko lau arrazoi egon daitezke:

1. definizioan genusik aurkitu ez izana (beharbada ez zeukalako)
2. genusa eduki bai, baina ezin desanbiguatu izatea
3. bigiztak apurtzean zintzilik geratzea
4. erlatore bidezko definizioetan, lotzen saiatu baina ezin izatea

Txapelaren bidez, beraz, lau arazo horiei erantzungo diegu modu integratu eta natural batean. VI.C.2 atalean ikusi dugu nola lotu HEBko adierak WordNet-i. Lotura horren emaitza bezala, kasu onenean, WordNet-eko kontzeptu bat izango dugu. Bestela, posible da kontzeptu bat baino gehiagotara lotzea. Bestalde, kode semantikoa ere esleitzen saiatu izan gara, eta hemen ere bi aukerak daude, hau da, kode semantiko bakarra edo gehiago edukitzea. Kontzeptuak lotzeko orduan honek aukera asko irekitzen dizkigu. Lan honetan hartu dugun hurbilpena sinpleena izan da, horren ekarpena ebaluatu eta aurrerago tratamendu konplexuagoak diseinatzeko. Lotzeko algoritmoa beraz horrelakoa izango da:

1. hierarkien erroak eta adiera isolatuak bildu
2. WordNet-eko kontzeptu bakarra badaukate esleituta, lotu kontzeptu horri
3. WordNet-eko kode semantiko bakarra badaukate esleituta, lotu kode semantiko horren kontzeptu adierazgarri bati
4. kontzeptu anitz eta kode semantiko anitz badituzte, utzi oraingoz

Txapelaren eraikuntzan hierarkien arteko erlazio konplexuak sor daitezke, hau da, bi hierarkia WordNet-eko kontzeptu berera lotuta egon daitezke, edo bata bestearen azpian dauden kontzeptuetara, etab. Lehen bezala, ez gara hemen ur handitan sartuko, eta ez dugu hierarkien loturen arteko harremanik kontuan hartuko.

VI.E.3. Ebaluazioa

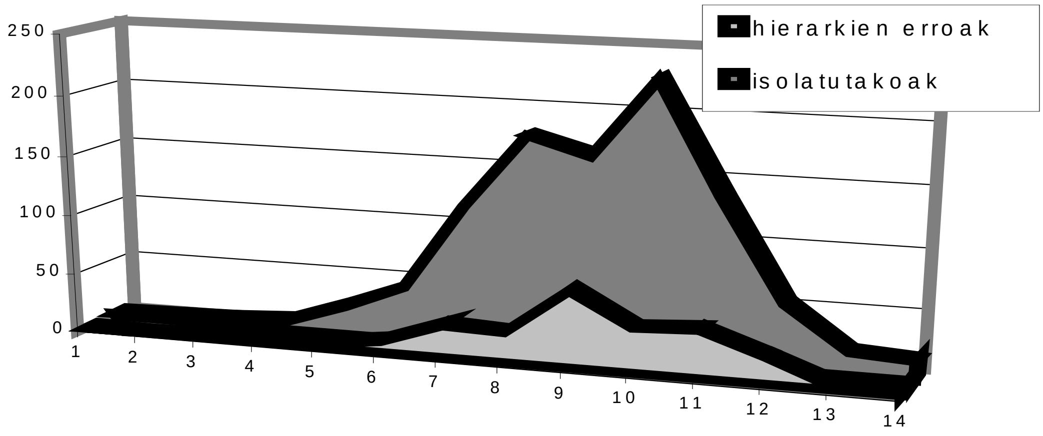
Lehenbizi hierarkien erroak eta adiera isolatuak bildu ditugu, eta horien loturak aztertu (ikus 45. taula). Aipatzekoa da hierarkien %15 bakarrik gelditu dela automatikoki lotzeko aukerarik gabe.

	Hierarkiako erroak		Isolatutakoak	
Kontzeptu bakarra	236	%45	991	%44
Kode semantiko bakarra	116	%22	353	%16
Anbiguoak	95	%18	145	%06
Lotura gabe	80	%15	769	%34
Guztira	527		2258	

45. taula: hierarkia eta adiera isolatuen loturak WordNet-era

Behin kontzeptu edo kode semantiko bakarra duten adierak lotu eta gero, hierarkiak eta isolatutako adierak WordNet-ko hierarkian integratzen dira. Lotura anbiguoa dutenentzat tratamendu bat egin beharko litzateke. Lotura honen fidagarritasuna aztertzeko, kontzeptu bakarrera lotuta daudenen lagin bat hartu dugu, 50 loturakoa, eta loturaren doitasuna %64koa bakarrik dela atera zaigu. Doitasun hau, LPPL-WordNet loturarako ditugun neurriak baino dezente apalagoa da (%80, ikus VI.C.2.f), ziur aski orain lotzen ari garen adierak, hierarkiatako erroak barne egonda, batezbestekoa baino orokor eta anbiguoagoak direlako. Eskuz aztertu ondoren, gehienak definizioan genus edo sinonimorik ez dutenak direla ikusi dugu, eta horrek LPPL-WordNet loturaren doitasun galtzean ere zer ikusia izan dezake.

WordNet-eko kontzeptu bakarrera lotu ditugun erro eta adiera isolatuei dagokionean, 28. irudian azaltzen da WordNet-eko zein sakoneratan kokatu diren. Ikusten den bezala, gehienak WordNet-eko alderdi sakonetan kokatu dira, 7 eta 11ko sakoneren artean. Isolatuentzat normala izan daiteke, baina hierarkien erroen kasuan adiera orokorragoak izatean, WordNet-eko goi aldean kokatzea espero zitekeen.



28. irudia: hierarkietako erroen eta adiera isolatuen kokapenaren sakonera WordNet-en

Aipatu ditugun datu hauek, loturaren doitasuna eta sakonera, hierarkiaren osatze guztiz automatikoa zalantzan jartzen dute. Loturak eskuz errepasatu beharko lirateke, hierarkiak WordNet-en dagozkion tokian kokatzeko. Dena den, 117 hierarkia zabalenek (10 adiera baino gehiago dituztenak) 10.127 adiera estaltzen dituzte, eta beraz, eskuzko lan gutxirekin hierarkia garrantzitsuenak lot daitezke.

Beharbada lotura finegia egiten saiatu gara, WordNet-eko kontzeptu mailan, eta egokiagoa litzateke lotura kode semantiko mailan egitea, asmatzeko aukera hobeagoak edukiko genituzke eta. Horretarako VI.C.2.e) atalean azaltzen diren kode semantikoak erabili zitezkeen. Hala egiten dute (Bruce et al., 1993) lanean, LDOCE-ko kode semantikoak erabiltzen baitituzte hierarkiak eta adiera isolatuak lotzeko.

VI.F. Ekarpenak

Kapitulu honetan ingelesa ez diren baliabide lexikal egituratuen eraikuntza sendotzeko teknikak landu ditugu. Izan ere, LPPL-tik erauzitako hierarkiak (Artola, 1993) ez dira libratzen hiztegietatik erauzitako hierarkiei egin izan zaizkien kritiketatik:

1. Hierarkia hitzen artekoa izatea, adieren artekoa izan ordez.
2. Hierarkietako bigiztak.
3. Erlatore bereziak hierarkian integratzeko arazoak.
4. Hierarkien sakonera apala eta goi mailako homogeneotasun falta.

Arazo horiek ebazteko bidean kanpoko ontologia baten beharra ikusi dugu, hierarkien goi-mailak antolatuko dituena eta hierarkia solteak lotzeko balioko duena. Bestalde, ontologia hori bigiztak hausteko eta erlatore bidezko definizioak hierarkian integratzeko ere erabili dugu. Planteatu diren 2., 3. eta 4. arazoak modu orokorrean konpontzeko metodoa aurkeztu dugu. Ontologia bezala WordNet erabili dugu, eta LPPL-ko adierak WordNet-era lotzeko tresna nagusi bezala Dentsitate Kontzeptuala erabili dugu.

1. arazoari dagokionean, behin LPPL-ko adierak WordNet-era lotu eta gero, genusak desanbiguatu ditugu, LPPL bertako informazioa eta LPPL-WordNet loturako informazioaz baliatuaz. Lortutako hierarkiak ebaluatu ditugu, bere horretan, eta gero LPPL-WordNet loturaz profitatuz, hierarkia guztiak lotu ditugu "txapela" kontzeptualaren bidez.

Egin diren lau zereginetarako garatu diren metodoak berritzaileak dira:

1. Bigizta eta erlatore bidezko definizioak tratatzekoa
2. LPPL-ko adierak WordNet-era lotzekoa
3. LPPL-ko genusak desanbiguatzekoa
4. Hierarkiak lotzekoa

VI.F.1. Bigizta eta erlatoreen tratamendua

Bigiztak puskatu eta hierarkian integratzeko modua aurkeztu dugu, LPPL-WordNet loturaz baliatzen dena. Aurkeztutako metodoari esker bigizta guztiak puskatzeko gai izan gara. Erlatoreen tratamenduari dagokionez, erlatore bidezko definizioen %78a hiperonimo desanbiguatu bati lotzea lortu dugu (LPPL-ko hierarkietan sartuz), eta %63 WordNet-eko adiera bati lotu. Erlatoreen kasuan, bai desanbiguazio eta bai WordNet-eko loturaren doitasuna %90era heldu dira. Emaitza hauei esker, bigiztak normal integratuko dira hierarkiatan, eta erlatore bidezko definizio gehienak edo hierarkian integratuta edo WordNet-i lotuta egongo dira. Geroago, hierarkiak lotzeko tratamenduari esker, WordNet-i bakarrik lotutako adiera horiek beste hierarkiekin ere lotu ahal izan ditugu.

VI.F.2. Kontzeptuen arteko lotura eleanitzak

LPPL-ko adierak WordNet-eko kontzeptuei lotzeko metodoa (elebiduna-WordNet) aurkeztu eta ebaluatu dugu. Metodo honi esker hizkuntza ezberdinetako baliabide lexikal egituratuak lotu daitezke kontzeptu/adiera mailan. Metodo honen emaitzak are hobeagoak izango lirateke hizkuntza bereko baliabideak lotuko balira, adibidez LDOCE eta WordNet lotuko balira.

Lehenbizi frantses-ingeles hiztegi elebidun bateko adierak WordNet-eko kontzeptuei lotu dizkiegu, horretarako Dentsitate Kontzeptuala soilik erabiliaz. Metodo horren bidez izenen adieren %43 lotu dugu %95eko doitasunarekin. Nahiz eta lan honetan garrantzi gehiegirik ez eman lotura hauei, ez bada LPPL-WordNet loturarako laguntza bezala, mota honetako loturak oso garrantzitsuak dira hizkuntza arrotzak ontologia jakin bati lotzeko. Izan ere guk garatutako metodo baino apalagoak erabili izan dira helburu horrekin, bai Sensus ontologiara gaztelerako hitzak lotzeko (Okumura & Hovy, 1994), bai EuroWordNet proiektuaren barruan gaztelerazko WordNet eraikitzeko (Rigau & Agirre, 1995; Atserias et al. 1997). Lan horietan tesi honetako metodoa aplikatuz gero, beraien doitasunak hobetuko liratekeela uste dugu.

LPPL-WordNet loturei dagokionean, elebiduna-WordNet loturek emaitzak hobetzeko balio izan du. Lotura horretaz gain, Dentsitate Kontzeptuala, hiperonimia erlazioak, heuristiko sinple batzuk eta nabarmentasunean oinarritutako hedadura erabili ditugu, erlatore berezien bidezko tratamendua barne. Horrela LPPL-ko izenen adieren %87 WordNet-era lotzea lortu dugu, batezbesteko %80ko doitasunarekin. Bai Dentsitate Kontzeptuala eta hiperonimia erlazioak WordNet-eko lotura paradigmatikoetan oinarritzen dira. *Nabarmentasun* bidezko metodoa, hiztegiko informazioaz eta WordNet-eko kode semantikoez baliatzen da, neurri estatistikoak erabiliz.

VI.F.3. Genus-desanbiguazioa

Gaurdaino hiztegietako genusen desanbiguazioa hierarkia zabal eta erabilgarriak automatikoki sortzeko arazo garrantzitsuena zela uste izan da. Arazo hau LDOCE hiztegirako bakarrik ebatzi izan da arrakastaz (%80ko doitasuna era guztiz automatikoan, %90 eskuzko laguntzari esker), hiztegiak adierentzat dauzkan kode pragmatiko eta semantikoei esker. Lan honetan erakutsi dugu genusen desanbiguazioa ez dagoela LDOCE-ra soilik mugatuta, bestelako lanetan ere bideragarria izan daitekeela, eta tesi honetarako garatutako metodoak LPPL hiztegirako %82ko doitasuna lortzen du. Beste edozein hiztegitara aplikatzeko balio du metodoak, eta hala frogatu izan da gaztelerarako DGILE (ikus II. kapitulua) hiztegian eginiko esperimentuetan, pareko doitasuna –%83– lortu izan baitugu (Rigau et al. 1997).

VI.F.4. Hiztegietatik erauzitako hierarkien lotzea

Doitasun handiko prozedura automatiko baten bidez erauzitako hierarkiak, nahiz eta bigizta eta erlatore bereziak behar bezala tratatu, badauzkate arazoak: hierarkia asko txikiak izan eta gainera solte daude, elkarrekin inongo loturarik eduki gabe. Gainera ezaguna da hiztegietatik erauzitako hierarkiek goi aldean duten egitura ez dela oso egokia. Bi arazo horiei automatikoki erantzuteko prozedura planteatu dugu, WordNet-era eginiko loturetaz baliatzen dena. Prozedura horretan hierarkietako erroak WordNet-era lotzen ditugu, horrela WordNet-en goiko geruzak ematen du koherentzia eta gainera hierarkia solte guztiak WordNet-en bidez lotuta gelditzen dira.

Planteatutako metodoa orokorra da, eta hiztegietatik erauzitako hierarkiak edozein ontologiatara lotzeko balioko luke, gehien interesatzen zaigun goi-maila hautatzeko aukera emanaz.

VI.G. Etorkizunerako lanak

Ekarpenetan egin dugun bezala, hemen ere atalka aztertuko ditugu aurrerantzean egin daitezkeen hobekuntza eta lanak. Lehenbizi lotura eleanitzak aipatuko ditugu. Ondoren genus desanbiguazioari buruz eta hierarkia isolatuak lotzeko metodoari buruz ihardungo dugu.. VI.G.4. Atalean lotura eleanitz eta genus desanbiguazioaren artean dagoen dependentzia funtzionala aipatuko dugu, izan ere, batak bestearen emaitza hobetu dezake, edo agian era integratu batean konpondu daitezke biak. Bukatzeko, ezagutza-base lexikalen sendotzeari buruzko lan orokorrak aipatuko ditugu.

VI.G.1. Kontzeptuen arteko lotura eleanitzak

Lotura eleanitzen hobekuntzari dagokionez, ez dago zalantzarik elebidun zabalago bat erabiltzeak emaitzak hobetuko lituzkeela. Alde batetik estaldura zabalagoa lortuko litzateke (eta elebiduna-WordNet-en kasuan estaldura hobeagoak zuzenean LPPL-WordNet loturaren doitasunaren hobekuntza dakar). Bestetik, LPPL-ko adieraren baterako itzulpenik ez egotea errore-iturri denez, elebidun zabalagoarekin halako gutxiago gertatuko lirateke, doitasuna ere hobetuz.

Elebiduna-WordNet loturaren estaldura jasotzeko beste modu bat frantsez-hitz/ingeles-hitz bikoteetan oinarritutako heuristikoak dira (Okumura & Hovy, 1994; Rigau & Agirre, 1995; Atserias et al. 1997). EuroWordNet proiektuan halako heuristikoak arrakastaz erabiltzen ari dira gaztelerarako WordNet-a eraikitzeko. Hala ere hitz bikote hauek badute murrizpenik, ez baitira hiztegi elebiduneko adierak kontuan hartzen. Horrek arazoak sortu ditzake: adibidez frantsesez monosemikoa den hitzak bi itzulpen ezberdin dituenean, eta itzulpen horiek kontzeptu ezberdinei dagozkienean. Beti ere azalduko zaizkigu, metodoa nola nahikoa izanda ere, hizkuntzen arteko *mismatch*-ak (Arregi 1995).

Elebiduneko adierak erabiltzeari esker, WordNet eta LPPL hiztegi elebidunetan dagoen informazio zabalarekin (Fontenelle, 1997) aberastu zitekeen. Arlo hau jorratzea interesgarria litzateke.

Gaur egun, EuroWordNet eta ITEM proiektuei lotuta, Euskararako WordNet-a ere eraikitzen ari gara, kapitulu honetan aurkeztutako teknikak eta arestian aipatutako hitz bikoteak euskara-ingelesa hiztegi elebidunari aplikatuaz. ITEM proiektuan gaztelerarako WordNet ere eraikitzen ari den heinean, hiztegi elebidunen kateak erabiliaz (euskara-gaztelera, euskara-ingelesa eta gaztelera-ingelesa) estaldura eta doitasuna hobetuko direlakoan gaude.

Kapitulu honetan garatutako metodoak baliabide lexikal egituratuak lotzeko balio duenez, ontologia eta EBLren bat egitean eragin handia izan dezake. Baliabide batek besteak duen ezagutza xurgatu eta ontologia aberatsagoak eraikitzen joateko bide egokia dirudi honek, *ANSI Ad Hoc Ontology Standards Group*[79] komiteak proposatzen duen bidea jarraituz (Hovy, 1997a; 1997b).

VI.G.2. Genus-desanbiguazioa

Nahiz eta lortu ditugun emaitzak oso onak izan, badago desanbiguazioaren doitasuna jasotzeko metodorik. (Rigau et al. 1998) artikuluan, kapitulu honetan azaldutako metodoa DGILE hiztegiari aplikatu ondoren (Rigau et al., 1997), genusak multzokatu egin genituen, WordNet-era lotzean lortu den kode semantikoaren arabera. Kode semantiko bakoitzerako genus usuenak bakarrik aukeratuaz doitasuna altxatu egiten da, estalduraren golkora. Hobekuntza hau LPPL-rekin egitea ere otu zitzaigun, noski, baina LPPL-ren neurri txikia dela eta genus usuenak ez ziren oso maiz gertatzen, eta ez genuen emaitzak hobetzerik lortu.

Bartzelonako UPC-ko lexikografia konputazionalean aritzen den taldeak eta gureak azterketa paraleloak egin ditugu, LPPL hiztegi txikiarentzat gurean, eta DGILE hiztegi zabalagoarentzat haienean. Hiztegien azterketa paralelo honetatik hiztegi txikietarako metodoak handietan ere balio izan digutela ondorioztatu daiteke. Gainera, hiztegi handietatik hierarkia zabalago eta interesgarriagoak jasotzen dira, eta orain aipatu dugun bezala, eta hobekuntzarako aukera gehiago ematen dituzte.

Bozketaren emaitzei dagokionean, bozketaren emaitzen azterketak oraindik hobekuntzarako tokia baduela uste dugu. Azterketa txiki batean ikusi genuen boza ematen dutenen artean gutxienez bosten adostasuna eskatuz gero %95eko doitasuna lortu genezakeela, baina estalduraren kaltetan (%18). Honek doitasun handiz egindako loturak identifikatzeko metodo bat eman lezake.

Bestalde, desanbiguazioa egitean definizioan bertan zegoen informazioa erabili dugu, baina hierarkien arteko desanbiguazioa ere planteatu daiteke, hau da, genus bat desanbiguatzerakoan, ziurtzat dauzkagun definiendumaren hiponimoak eta genusaren adiera bakoitzaren beste hiponimo eta hiperonimoak ere kontuan har ditzakegu.

Ildo berean, behin "txapela" eginda ere, errazagoa izan daiteke genus desanbiguazioa egitea.

[79] http://ksl-web.stanford.edu/onto-std/

VI.G.3. Hiztegietatik erauzitako hierarkien lotzea

Tesi-lan honetan hierarkien eraikuntzan sinonimia erlazioa ez dugu kontuan hartu. Autore gehienek hiztegietatik erauzitako sinonimia erlazioari ez diote jaramonik egin, baina LPPL-ren kasuan sinonimo bidezko definizioak ugariak dira (adiera guztien %20). Artolak (1993) bere HEBan sinonimo ziren adieretan erlazioak sinonimo batetik bestera kopiatzen zituen, eta horren eragina neurtzea interesgarri deritzogu. Bestelako hurbilpenak, adibidez WordNet-en sinonimo diren adiera guztiak kontzeptu bakarra osatzen dute, ere aztertu beharko lirateke.

Nahiz eta hierarkiak lotzeko metodoak etorkizuna duela erakutsi dugun, ez dugu zehatz-mehatz ebaluatu lortzen den hierarkiaren kalitatea. Halakoak ebaluatzeko ez dago gaur egun irizpide finkorik, ez bada hiponimo/hiperonimo lotura bakoitzaren doitasuna, jadanik eman duguna (%82). Neurri hori oso mugatua izanda, aplikazio batetarako –adibidez, informazioaren erauzketa– erabilgarria den edo ez izan daiteke irizpide interesgarria. Bestalde ezin da ahaztu *ANSI ad hoc Ontology Standards Group* delakoa, arestian aipatu duguna, bere zereginen artean ontologiak ebaluatzeko irizpideak lantzen ari dela, oraingoz emaitza gabe.

VI.G.4. Sorgin-gurpila

Gure hurbilpena aurkeztean (ikus VI.A.5 atala), aipatu izan dugu kapitulu honetan azaltzen diren hiru prozeduren artean, LPPL-WordNet lotura, LPPL-ko genusen desanbiguazioa eta LPPL-ren txapelaren eraikuntza, elkarrekintza konplexuak gerta zitezkeela. Horien azterketari ezin genion eutsi lehenbizi hiru prozedurak ez bagenituen era independentean egiten, edo hobeto esanda, LPPL-WordNet lotura bere kabuz egin, LPPL-ko genusen desanbiguazioa bere kabuz egin (LPPL-WordNet lotura erabiliaz ere), eta txapela aurreko bien emaitzen gainean egin.

Hiru prozesuen arteko elkarrekintza hobeto aztertu beharko dugu. Orain arte egindakoaren informazioa hor dago beste modu batzuetara konbinatzeko. Adibidez, behin LPPL-ko hierarkiak desanbiguatu eta txapelaren bidez lotu ondoren, LPPL-WordNet lotura egiteko informazio gehiago dugu, hierarkiak lotzen ari baikara, eta suposatu daiteke emaitza hobeagoak lortu ditzakegula. Bestalde jadanik aipatu dugu, behin txapela eginda, errazagoa izan daitekeela genus desanbiguazioa egitea. Lotura elebidun hobeekin, bai txapela eta bai genus desanbiguazioa ere hobetu daitezke, eta abar. Honekin prozesu iteratibo bat plantea daiteke.

Bestelako hurbilpen interesgarri bat sare neuronalen eskutik etorri daiteke. Kapitulu honetan deskribatutako emaitza guztiak –LPPL-WordNet lotura, LPPL-ko hiponimo/hiperonimo erlazioak, WordNet beraren hierarkia– sare neuronal bateko arku bezala errepresenta daitezke. Sare neuronalari energia-funtzio egoki bat esleituz gero, ezagunak diren teknikak aplikatu daitezke arkuen konbinazio ezin hobea bilatu dezan. Horrela aldi berean erabakiko luke zein den adiera bakoitzerako WordNet-lotura hoberena eta hiperonimo hoberena.

VI.G.5. Bestelakoak

EBLen sorkuntza eta aberasketa automatikoa landu dugun arren, ez ditugu horren ikuspuntu guztiak landu. Hutsune nagusietako bat definizioen *differentia*-tik erauzitako informazioa (Artola, 1993) landu ez dugula izan da. V.B atalean LPPL-ko definizioen *differentia-tik* erauzitako erlazioen adibideak ikusi ditugu. *Differentia-ren* erabilera betidanik interesgarritzat jo izan da eta lan berriek (ikus adibidez, Richardson, 1997) arnas berria eman diote bertatik erauzitako informazioaren erabilgarritasunari. Bestalde, adieren adibideen analisiak ere informazio interesgarria eman dezakeela uste dugu, adiera azaltzen den testuinguruei buruzko informazio interesgarria ematen dute eta.

Euskarari dagokionean, ezin dugu aipatu gabe utzi Euskal Hiztegiaren gainean gure taldean egiten ari den lana. Lan horren helburua euskararako ezagutza-base zabala sortzea, informazio semantikoan aberatsa. Horretarako hiztegiaren egituraren azterketa egin da eta TEI gidalerroak jarraitzen dituen kodeketara itzuli dugu (Arriola et al. 1995; 1996a; 1996b). Jadanik bukatu dugu izenen definizioetako erlatore berezi eta genusen bilaketa (Agirre et al. 1998), eta gaur egun aditz eta adjektiboen analisia, adieren adibideen analisia, eta WordNet-en lotura lantzen ari gara. Hurrengo pausoan, kapitulu honetan azaldutako metodoen bidez, izen, aditz eta adjektiboen hierarkien eraikuntzari ekingo diogu, taldeko kide baten tesiaren barruan, atal honetan planteatu ditugun hobekuntzak aplikatzen saiatuz. Bestalde, Euskal Hiztegiko definizioetan erabiltzen den hizkuntzaren azterketa ere martxan dago, oraingo genus eta erlatore bidezko bilaketa bezala. Etorkizun laburrean. taldean garatzen ari diren gramatiken bidez, *differentia*-ren azterketari ekingo diogu, taldeko beste kide baten tesia izango den lanean.

Azkenik, interesgarritzat jotzen dugu hierarkia eleanitzen eraikuntza automatikoa. Hizkuntza ezberdinetako baliabideak lotzen goazen heinean, hierarkia eleanitzak osatzen ari gara. Inplizituki, ontologia ezberdinetako informazio (erdi-)automatikoki hizkuntza batetik bestera xurgatzea posiblea den edo ez aztertzen ari gara, eta aldi berean hierarkia unibertsalak eraiki daitezkeen edo ez aztertzen. Aldi berean, hierarkia ezberdinetako informazioa bateragarria den edo ez, goi mailak automatikoki lotzea komeni ote den, eta antzeko galdera ugari sortzen zaizkigu. Galdera hauek baliabide lexikal egituratuen eraikuntzatik munduaren eta hizkuntzen ereduen azterketara garamatzate.

VII.Kapitulua
ONDORIOAK

VII.A. Sarrera

Lan honen ekarpen nagusiak bi dira:

1. Erlazio-izaeraren formalizazioa: Dentsitate Kontzeptuala
2. Hiztegietatik erauzitako hierarkiak trinkotzeko metodoa

Lan honetan izenen adieren arteko erlazio-izaeraren neurri bat formalizatu dugu: Dentsitate Kontzeptuala. Neurri hau ontologietan oinarritzen da, eta beraz LNPan erabiltzen den informazioa berrerabiltzen du. Edozein ontologiara aplikatu daiteke, ez du behar inongo aurre-prestaketarik, eta ontologiak estaltzen dituen domeinu guztietan lan egiteko gauza da. Dentsitate Kontzeptualaren inplementazio osoa WordNet gainean egin dugu.

Gure formalizazioa interesgarriagoa dela defendatu dugu, bai beste baliabide lexikaletan oinarrituta dauden neurrien aurrean (corpus eta hiztegi), baita ontologiatan oinarritzen diren bestelako neurrien aurrean ere. Nagusitasun hori praktikan erakusten saiatu gara:

- Hitzen Adiera-Desanbiguazioan (IV. kapitulua)

- Testuen Zuzenketa Automatikoa (V. kapitulua)

Hitzen adiera-desanbiguazioan emaitza onak lortzen ditu, nahiz eta nahiko zaila izan beste sistemekin konparatzea. Hobeto konparatu ahal izateko ontologian oinarritutako beste bi sistema inplementatu, eta Dentsitate Kontzeptualak beraien emaitzak gainditzen dituela ikusi dugu. Zuzenketa automatikoari dagokionez emaitzak bestelakoak izan dira. Dentsitate Kontzeptuala izenei besterik aplikatu ezin denez, zuzenketa proposamen guztiak izenak direnean bakarrik aplikatu ahal izan dugu, eta beraz, nahiz eta erabili diren ebaluazio corpusak zabalak izan, Dentsitate Kontzeptualak oso gutxitan hartu du parte. Aurkeztu dugun zuzenketa automatikorako sistemak beste ezagutza-iturrietara ere jo du.

Bestalde, hiztegietatik erauzitako hierarkiak sendotzeko metodo bat aurkeztu dugu. Metodo honek Dentsitate Kontzeptuala eta landutako hiztegiko bertako ezagutza ere erabiltzen ditu. Maila praktikoan bi hobekuntza nabari burutu ditugu:

- *Le Plus Petit Larousse* frantses hiztegiko adierak WordNet-i lotu
- *Le Plus Petit Larousse*-etik erauzitako HEBko adieren hierarkiak desanbiguatu eta trinkotu

Lehenbizikoari esker, eraikitako hierarkia horien gabezia batzuk konpon ditzakegu, WordNet-eko hierarkia erabiliz goi-ontologia bezala: definizio erlazionalak lotzeko, bigiztak ebazteko, hierarkia isolatuak elkarren artean lotzeko eta hierarkiei goi-maila koherente bat emateko. Aurkeztu dugun metodoa edozein hiztegitatik erauzitako hierarkiak desanbiguatu eta trinkotzeko erabil daiteke. Bestalde, baliabide lexikalak ezkontzeko ere balio duenez, baliabide heterogeneoak, hizkuntza berekoak edo ez, bat egiteko erabil daiteke: ontologiak EBLetara, EBLak EBLetara eta abar. Honek perspektiba berriak irekitzen ditu baliabide lexikalen aberasketan, ezagutzan pobre den hizkuntza batek ingeleserako eraikitako ezagutza xurgatu dezake eta. Betiere, kontu izanez ekartzen den ezagutza hizkuntza horretarako baliagarria den edo ez, noski. Hitzen adiera-desanbiguazioa ere, hein handi batean, baliabide lexikalen lotzea bezala ikus daiteke, corpuseko hitzak ontologia bateko adiera/kontzeptuetara lotzen baitira. Ikuspegi honek ontologiak aberasteko bide berriak irekitzen ditu.

Etorkizunerako lanari dagokionez, behar handia ikusten dugu ontologia zabal eta aberatsak sortzeko. Izan ere, Dentsitate Kontzeptualaren bidez WordNet-ek duen informazioaz besterik ezin gara baliatu, hau da, batez ere erlazio paradigmatikoak. Nahiz eta horrela ere emaitza onak lortu aplikatu dugun zereginetan, garbi dago erlazio sintagmatikoak ere beharrezkoak direla, adibidez, hitzen adiera-desanbiguazioa hobetzeko, baina bereziki zuzenketa automatikoan Dentsitate Kontzeptualaren ekarpena zabaltzeko.

HAD egiteko, baina LNParen bestelako arazo lexikal-semantikoei irtenbide sendoa emateko ere, corpus, hiztegi eta ontologien arteko koordinazio estua behar dela uste dugu. VI. kapituluan ontologia, EBLak eta HEBak lotu eta bat egitea posible dela agertu dugu. Horrelako integrazioak WordNet aberasteko balio dezake, baina, hala ere, ez litzateke nahikoa izango HADrako beharrezko ezagutza guztia biltzeko. Adibidez, hiztegi zabal baterako hautapen-murrizpenen zerrendarik ez dago eskuragarri inon. Holakoen ikasketa bultzatzeko hiztegiko definizioen analisia eta erabilera indartu behar da (adibidez, VI. kapituluan aipatutako teknikak erabiliaz), ondoren, definizioko hitzen adierak desanbiguatuta daudenean, ontologietan integratu ahal izateko ezagutza hori. Berdintsu gertatzen da corpusekin. V. kapituluan ikusi dugu corpusetan oinarritutako neurri estatistikoek ere hitzen arteko erlazio-izaeraren neurria ondo islatzen dutela, eta ezagutza hori ontologietan integratzeko moduan kodetu beharko litzatekeela. Hitzen adiera-desanbiguazioaren bidez, hain zuzen ere, posible izan beharko litzateke hitzen arteko erlazio horiek adieren arteko bihurtzea, eta horrela ontologiari lotu. Dentsitate Kontzeptuala modu egoki batera hedatuz, ontologia mota berri horietako erlazioez profitatuko litzateke, errepresentazio trinko eta eraginkor baten bidez, iturri ezberdin askotako ezagutza erabiliaz erlazio-izaera kalkulatu ahal izateko.

Azter ditzagun era zabalago batean kapitulu bakoitzean eskaini ditugun ekarpen nagusiak, eta ondoren etorkizunerako lanak ikusiko ditugu.

VII.B. Ekarpenak

VII.B.1. Erlazio-izaeraren neurria definitu: Dentsitate Kontzeptuala (III. kapitulua)

Dentsitate Kontzeptuala diseinatu eta inplementatu dugu, ontologietan oinarrituaz erlazio-izaera formalizatzeko. Dentsitate Kontzeptuala ontologiako erlazio paradigmatikoetaz –hiperonimia eta meronimia– baliatzen da, eta izenekin lan egiten du oraingoz, nahiz eta aditzetarako ere egokia izan daitekeen.

Ontologietan oinarritzen diren gainontzeko formalizazioen ezaugarriak dauzka. Oinarri teoriko sendoa du, adimen artifizial eta psikolinguistikan ezagutzaren errepresentaziorako eredu nagusiak baitira ontologiak. Adieren arteko neurria eskaintzen digu, adiera horien definizio sendoa eskainiz, adierak ontologiako kontzeptuei lotuta daude eta. Bestalde ez du eskuzko desanbiguazio beharrik, ez eta datu urrien edo gehiegizkoen arazorik. Ezaugarri hauek dira ontologietan oinarritutako neurriak, corpus eta hiztegietan oinarritutakoekin alderatuz gero, dituzten abantailak.

Ontologietan oinarritutako neurriak, aldiz, eraginkortasun-arazoak eduki ohi dituzte. Gainera erlazio-izaeraren neurriak bi kontzepturen artekoak, eta ez gehiago, izaten dira. Dentsitate Kontzeptualak ez dauzka murrizpen horiek, eta beraz, ontologietan oinarritzen diren beste neurriak gainditzen ditu. Edozein kontzeptu kopururen erlazio-izaera neurtu dezake, gainera kopuru ezberdineko multzoen neurriak konparatzeko modua eskainiaz. Testu zabalekin lan egiteko bezain eraginkorra da.

VII.B.2. DKaren aplikazioa: hitzen adiera-desanbiguazioa (IV kapitulua)

WordNet-eko ezagutza paradigmatikoa darabilen Dentsitate Kontzeptualean oinarritutako desanbiguatzailea eraiki eta probatu dugu. Dentsitate Kontzeptualaren ezaugarriei esker ontologiako adieren arabera desanbiguatzeko gai den sistema eraiki dugu, testu errealetako izenak denbora mugatuan desanbiguatzeko gai dena. Edozein testutara aplikatu daiteke, inongo egokitzapenen beharrik gabe.

Esperimentuko emaitzen arabera, Dentsitate Kontzeptuala HADrako erabilgarria dela frogatu dugu, eta WordNet-eko ezagutzaz erlazio-izaera paradigmatikoen beste formalizazioak –Sussna (1993) eta Yarowsky (1992)– baino hobeto baliatzen dela erakutsi ere bai.

HADaren literaturan azaltzen diren esperimentuekin alderatzean gure esperimentuak arazoaren alde zailenari egin dio aurre: adiera bereizketa xeheak, domeinu ezberdinetako testu errealak, testuko izen guztiak, emaitza partzialak baztertuaz eta adiera bakarra ontzat emanaz. Testuak (guztira 10.000 hitz) ez ziren inolaz ere errazak desanbiguatzeko. Hala ere, WordNet-eko adiera finetarako desanbiguatzean %64ko doitasuna lortzen dugu, eta fitxategi-mailan desanbiguatzen badugu %71koa. Estaldura oso zabala da, testuetako izenen %86 desanbiguatzen dugu eta.

VII.B.3. DKaren aplikazioa: zuzenketa automatikoa (V. kapitulua)

Testu-zuzenketa automatikoa egiten duen sistema diseinatu eta eraiki dugu, ez-hitz motako sakatze-erroreentzat proposamen egokia aukeratzen duena. Alde batetik zuzenketa automatikoa gaur egungo teknologiaren eskura dagoela frogatu dugu, eta bestetik Dentsitate Kontzeptualaren ekarpena apala izan dela ikusi dugu.

Sistema honek ezagutza-mota ezberdinak konbinatzen ditu: sintaktikoa (Murrizpen-Gramatikak), semantikoa (Dentsitate Kontzeptuala), hitzen maiztasunak, testuinguru-estatistikak eta heuristiko espezifikoak. Murrizpen-Gramatika, Dokumentuko Maiztasun eta Testuinguru-Estatistikei esker, gai da 25 erroretatik 24etan proposamen bakarra aukeratzeko (bestela bi proposamen) %90eko doitasunarekin, eta errore **guztientzat** erantzuten du. Emaitza hauek frogatzen dute zuzenketa automatikoa egingarria izan daitekeela.

Dentsitate Kontzeptualaren estaldura erroreen %8koa izan da soilik, proposamen guztiak izenak direnean bakarrik aplikatzen da eta. Lagin txiki horrekin fidagarritasun gutxiko datua izanda ere, %75eko doitasuna lortu da. Doitasun apal honen arrazoia ez da DKarena berez, erabilitako WordNet ezagutza-basearen gabeziena baizik, III. kapituluan arrazonatu dugun bezala.

VII.B.4. Baliabide lexikalak sendotu (VI. kapitulua)

Kapitulu honetako sarreran aipatu ditugu hiztegietatik erauzitako hierarkiak dituzten arazoak, eta *Le Plus Petit Larousse*-etik erauzitako hierarkiak ere (Artola, 1993) ez dira horretatik libratzen. Arazo horiek ebazteko bidean kanpoko ontologia baten beharra ikusi dugu, hierarkien goi-mailak antolatuko dituena eta hierarkia solteak lotzeko balioko duena. Bestalde, ontologia hori bigiztak konpondu eta erlatore bidezko definizioak hierarkian integratzeko ere erabili dugu. Kanpoko ontologia hori izan da ere hierarkiako hitzak desanbiguatzeko giltza. Lau zereginetan banatu dugu hierarkiak aberastu eta trinkotzeko metodoa:

VII.B.4.a) Bigizta eta erlatoreen tratamendua

Bigiztak puskatu eta hierarkian integratzeko modua aurkeztu dugu, LPPL-WordNet loturaz baliatzen dena. Aurkeztutako metodoari esker bigizta guztiak puskatzeko gai izan gara. Erlatoreen tratamenduari dagokionez, erlatore bidezko definizioen %78a hiperonimo desanbiguatu bati lotzea lortu dugu (LPPL-ko hierarkietan sartuz), eta %63 WordNet-eko adiera bati lotu. Erlatoreen kasuan, bai desanbiguazio eta bai WordNet-eko loturaren doitasuna %90era heldu dira. Emaitza hauei esker, bigiztak normal integratuko dira hierarkiatan, eta erlatore bidezko definizio gehienak edo hierarkian integratuta edo WordNet-i lotuta egongo dira. Geroago, hierarkiak lotzeko tratamenduari esker, WordNet-i bakarrik lotutako adiera horiek beste hierarkietara lotu ahal izan ditugu.

VII.B.4.b) Hizkuntza ezberdinetako baliabideen lotura kontzeptu mailan

Lehenbizi frantses-ingeles hiztegi elebidun bateko adierak WordNet-eko kontzeptuei lotu dizkiegu (elebiduna-WordNet), horretarako Dentsitate Kontzeptuala soilik erabiliaz. Metodo horren bidez izenen adieren %43 lotu dugu %95eko doitasunarekin. Mota honetako loturak oso garrantzitsuak dira hizkuntza arrotzak ontologia jakin bati lotzeko. Izan ere guk garatutako metodo baino apalagoak erabili izan dira helburu horrekin, bai Sensus ontologiara gaztelerako hitzak lotzeko (Okumura & Hovy, 1994), bai EuroWordNet proiektuaren barruan gaztelerazko WordNet eraikitzeko (Rigau & Agirre, 1995; Atserias et al. 1997). Lan horietan tesi honetako metodoa aplikatuz gero, beraien doitasunak hobetuko liratekeela uste dugu.

LPPL-ko adierak WordNet-eko kontzeptuei lotzeko metodoari dagokionean (LPPL-WordNet), elebiduna-WordNet loturek emaitzak hobetzeko balio izan dute. Lotura horietaz gain, Dentsitate Kontzeptuala, hiperonimia erlazioak, heuristiko sinple batzuk eta nabarmentasunean oinarritutako hedadura erabili ditugu, erlatore berezien bidezko tratamendua barne. Horrela LPPL-ko izenen adieren %87 WordNet-era lotzea lortu dugu, batezbesteko %80ko doitasunarekin. Bai Dentsitate

Kontzeptuala eta hiperonimia erlazioak WordNet-eko lotura paradigmatikoetan oinarritzen dira. Nabarmentasun bidezko metodoa, hiztegiko informazioaz eta WordNet-eko kode semantikoez baliatzen da, neurri estatistikoak erabiliz.

VII.B.4.c) Genus-desanbiguazioa

Lan honetan erakutsi dugu genusen desanbiguazioa ez dagoela LDOCE-ra soilik mugatuta., eta tesi honetarako garatutako metodoak LPPL hiztegirako %82ko doitasuna lortzen du. Beste edozein hiztegitara aplikatzeko balio du metodoak, eta hala frogatu izan da gaztelerarako DGILE (ikus II. kapitulua) hiztegian eginiko esperimentuetan, pareko doitasuna –%83– lortu izan baitugu (Rigau et al. 1997).

VII.B.4.d) Hiztegietatik erauzitako hierarkien lotzea

Automatikoki sortutako hierarkiek badauzkate arazoak: gehienak txikiak dira eta gainera solte daude, elkarrekin inongo loturarik eduki gabe. Gainera ezaguna da hiztegietatik erauzitako hierarkiek goi aldean duten egitura ez dela oso egokia. Bi arazo horiei automatikoki erantzuteko prozedura planteatu dugu, WordNet-era eginiko loturetaz baliatzen dena. Prozedura horretan hierarkietako erroak WordNet-era lotzen ditugu, horrela WordNet-en goiko geruzak ematen du koherentzia eta gainera hierarkia solte guztiak WordNet-en bidez lotuta gelditzen dira. Planteatutako metodoa orokorra da, eta hiztegietatik erauzitako hierarkiak edozein ontologiatara lotzeko balioko luke, gehien interesatzen zaigun goi maila hautatzeko aukera emanaz.

VII.C. Etorkizunerako lana

VII.C.1. Dentsitate Kontzeptualaren hobekuntza (III. kapitulua)

Dentsitate Kontzeptuala hobetzeko hiru alor nagusi hauek ikusten ditugu:

- Darabilen informazioari dagokiona: erlazio sintagmatiko eta hautapen-murrizpenak dituen ontologia bat lortu edo WordNet bera halakoez aberastu. Tamalez gaur egun informazio hori ez dago zuzenean eskuragarri, baina hiztegi eta corpusetatik automatikoki eskuratzeko metodoak ikertzen ari dira. VI. kapituluan aipatu dugu, adibidez, hiztegietako *differentia-ren* azterketatik erauztea posible dela. Zuzenketa automatikorako kapituluan ere ikusi dugu corpusetatik erauzitako Testuinguru-Estatistikek darabilten informazio gordinean, modu inplizituan bada ere, erlazio sintagmatiko eta hautapen-murrizpenak ezkutatzen direla. Baliabide lexikalen integrazioari (VI. kapitulua) eta adiera-desanbiguazioari (IV. kapitulua) esker, informazio hori WordNet ontologian integratu ahal izango litzateke.

- Formulari dagokiona: Dentsitate Kontzeptualaren formula aldatu, paradigmatikoak ez diren erlazioak kontuan har ditzan. V.B.2 atalean labur azaldu dugu nola integratu zitezkeen erlazio sintagmatikoak Dentsitate Kontzeptualean, (Agirre et al. 1994b) lanak LPPL-tik erauzitako erlazio paradigmatiko eta sintagmatikoak Distantzia Kontzeptualaren bidez erabiltzeko proposamenaren ildotik doana.

- Inplementazioa azkartu: nahiz eta Dentsitate Kontzeptualaren algoritmoa konplexutasun gehiegizkoa ez izan, egungo inplementazioa baina azkarrago bat lor daitekeela uste dugu. Horren arrazoietako bat LISP lengoaiaz inplementatuta egotea da, eta bestea WordNet-eko informazioaren atzipena ez dagoela optimizatuta. Egun, C++ lengoaiaz inplementatutako bertsio bat lantzen ari gara, UNED-eko Elektrizitate eta Elektronika saileko ikerkuntza taldearekin batera, ITEM[80] proiektuaren barruan. Bertsio hau ingeniaritza linguistikorako GATE[81] ingurunearen barruan (Cunningham et al. 1997) integratuta egongo da laster, hitzen adiera-desanbiguaziorako moduluaren barruan.Inplementazioa azkartu.

VII.C.2. Hitzen adiera-desanbiguazioa (IV. kapitulua)

Egindako esperimentuetan baziren hobetu zitezkeen alor batzuk:

- Diskurtso-egituraren araberako testu zatiak batera desanbiguatu. Horrela egin izanez gero hitzak bakarka desanbiguatu ordez testu zati oso bat batera desanbiguatu zitekeen, eraginkortasun hobeagoa lortuaz. Gainera doitasuna ere hobetuko litzateke, zerikusirik ez duten testu zatiak alde batera utziko ziren eta.

- Dentsitatearen neurri eta adiera-aukeraketaren artean koerlaziorik ote dagoen ikertzea interesgarria izango litzateke. Koerlazioa balego Dentsitatearen balio batetik behera daudenak desanbiguatu gabe utzi eta doitasuna hobetuko litzateke (estaldura gutxitzearen truke).

HADrako sistema ahaltsuago bat egin nahi bada, erlazio-izaeraz gain desanbiguazioan erabilgarriak diren bestelako informazio iturriak (IV.A.1 atalean aipatu bezala) ere erabiltzea beharrezkoa da. Honen adibideak dira, adieren maiztasunak, bai orokorrean edo desanbiguatzen ari garen testuan, adiera beti kolokazio modura azaltzen ote den, adiera bakoitzaren inguruan dagoen egitura sintaktikoari buruzko informazioa, eta abar. Horrela adiera-desanbiguaziorako sistema osoago bat eraikiko genuke, Dentsitate Kontzeptualaren bidez informazio lexikal-semantikoa kodetzen duena, eta hau bestelako ezagutzarekin konbinatzeko gai dena.

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80 http://sensei.ieec.uned.es/item/

81 http://www.dcs.shef.ac.uk/research/groups/nlp/gate/

Tesi hau idazten ari garen bitartean, SENSEVAL txapelketa[82] gertatzen ari da. Mundu mailan adiera desanbiguatzen duten sistemek parte hartzen dute. Txapelketa horretarako, Yarowsky-ren (1995) lana, Dentsitate Kontzeptuala eta hiztegietan oinarritutako bestelako erlazio-izaeraren neurriak (VI. kapituluan azaldu ditugunak) integratzen saiatzen ari gara.

VII.C.3. Zuzenketa utomatikoa (V. kapitulua)

Esperimentua diseinatzeko orduan ez genuen kontuan hartu ikasteko corpusa (Brown) eta probatzekoa (Bank of English) dialekto ezberdinekoak zirenik. Ziurra da arazo honek maiztasun orokorrak erabiltzen dituen heuristikoaren eta Testuinguru-Estatistikak erabiltzen dituenaren emaitzak kaltetu dituela. Komenigarriena Bank of English corpuseko bertako datuetatik ikastea izango litzateke, baina tamalez datu horiek eskuratzeko murrizpen gogorrak daude. Murrizpen hauen ondorioz errore errealen corpusak oso testuinguru txikia zeukan errorearen inguruan. Horrek modu erabakiorrean kaltetu du Dokumentuko Maiztasunen teknika, bestela oso indartsua zena. Arazo horiek konpondu ondoren doitasuna nabari hobetuko delakoan gaude.

Zuzenketa automatikoaren doitasuna hobetzeko beharrezkoa da erabilitako ezagutza fintzea. Murrizpen-Gramatika, adibidez, erroreak dituzten testuetara hobeto egokitu daiteke, guk erabili dugun bertsioa ez baitzegoen horretarako diseinatua. Dentsitate Kontzeptuala ere, arestian aipatu bezala aberastuz gero, emaitza hobeagoak espero daitezke. Bestalde, WordNet-en aberasketak Dentsitatea kategoria ezberdineko kontzeptuetara zabalduko luke, eta horrela Dentsitateak zuzenketan zuen estaldura areagotu.

Bukatzeko, kapitulu honetako emaitzek ez dute berretsi III. kapituluan aipatu dugun Dentsitate Kontzeptualaren ezaugarrietako bat: hitzen arteko erlazio-izaera neurtzeko baliagarria izatea. Zuzenketa automatikorako erabili dugun algoritmoan adieren arteko Dentsitate handiena zuten proposamena hautatu dugu, baina bestelako konbinazioak ere probatu beharko genituzke, adibidez, proposamen bakoitzaren adiera guztien Dentsitatea batu eta batura handiena duen hitza aukeratu proposamen egoki bezala.

VII.C.4. Baliabide lexikalak areago sendotu (VI. kapitulua)

VII.C.4.a) Kontzeptuen arteko lotura eleanitzak

Hiztegi elebidun zabalagoak erabiliz gero estaldura eta doitasun hobeak lortuko lirateke LPPL-WordNet loturan: alde batetik elebiduna-WordNet zabalagoa edukiko genukeelako, eta bestetik,

[82] http://www.itri.bton.ac.uk/events/senseval/cfp2.html

LPPL-ko adieraren baterako itzulpenik ez egotea errore-iturri denez, elebidun zabalagoarekin halako erroreak gutxituko lituzkeelako.

Elebiduna-WordNet loturaren estaldura jasotzeko beste modu bat frantsez-hitz/ingeles-hitz bikoteetan oinarritutako heuristikoak dira (Okumura & Hovy, 1994; Rigau & Agirre, 1995; Atserias et al. 1997). EuroWordNet proiektuan halako heuristikoak arrakastaz erabiltzen ari dira gaztelerarako WordNet-a eraikitzeko. Hala ere hitz bikote hauek badute murrizpenik, ez baitira hiztegi elebiduneko adierak kontuan hartzen, eta horrek arazoak sortu ditzake.

Adiera elebidunak erabiltzeari esker, WordNet eta LPPL hiztegi elebidunetan dagoen informazio zabalarekin (Fontenelle, 1997) aberastu zitekeen. Arlo hau jorratzea interesgarria iruditzen zaigu.

Gaur egun, EuroWordNet eta ITEM proiektuei lotuta, Euskararako WordNet-a ere eraikitzen ari gara, VI. kapituluan aurkeztutako teknikak eta arestian aipatutako hitz bikoteak euskara-ingelesa hiztegi elebidunari aplikatuaz. ITEM proiektuan gaztelerarako WordNet ere eraikitzen ari den heinean, hiztegi elebidunen kateak erabiliaz (euskara-gaztelera, euskara-ingelesa eta gaztelera-ingelesa) estaldura eta doitasuna hobetuko direlakoan gaude.

Atal honetarako garatutako metodoak baliabide lexikal egituratuak lotzeko balio duenez, ontologia eta EBLen bat egitean eragin handia izan dezake. Baliabide batek besteak duen ezagutza xurgatu eta ontologia aberatsagoak eraikitzen joateko bide egokia dirudi honek, *ANSI Ad Hoc Ontology Standards Group*[83] komiteak proposatzen duen bidea jarraituz (Hovy, 1997a; 1997b).

VII.C.4.b) Genus-desanbiguazioa

Nahiz eta lortu ditugun emaitzak oso onak izan, badago desanbiguazioaren doitasuna altxatzeko metodorik. Berriki (Rigau et al. 1998) artikuluan azaldu dugun bezala, VI. kapituluan azaldutako metodoa DGILE hiztegiari aplikatu ondoren, genusak multzokatu egin genituen, WordNet-era lotzean lortu den kode semantikoaren arabera. Kode semantiko bakoitzerako genus usuenak bakarrik aukeratuaz doitasuna altxatu egiten da, estalduraren golkora. Hobekuntza hau LPPL-rekin egitea ere otu zitzaigun, noski, baina LPPL-ren neurri txikia dela eta genus usuenak ez ziren oso maiz gertatzen, eta ez genuen emaitzak hobetzerik lortu.

Bartzelonako UPC-n lexikografia konputazionalean aritzen den taldearekin batera egindako ikerkuntzak hiztegi txikietarako metodoak handietan ere balio izan digutela ondorioztatu du. Hiztegi

[83] http://ksl-web.stanford.edu/onto-std/

handietatik hierarkia zabalago eta interesgarriagoak jasotzen dira, eta hobekuntzarako aukera gehiago eskaintze dute.

Bozketaren emaitzei dagokionean, bozkatzeko modu sofistikatuagoak erabiltzea aztertzea interesgarria dela uste dugu. Azterketa txiki batean ikusi genuen boza ematen dutenen artean gutxienez bosten adostasuna eskatuz gero %95eko doitasuna lortu genezakeela, baina estalduraren kaltetan (%18).

Bestalde, desanbiguazioa egitean definizioan bertan zegoen informazioa erabili dugu, baina hierarkien arteko desanbiguazioa ere planteatu daiteke, hau da, genus bat desanbiguatzerakoan, ziurtzat dauzkagun definiendumaren hiponimoak eta genusaren adiera bakoitzaren beste hiponimo eta hiperonimoak ere kontuan har ditzakegu.

Ildo berean, behin "txapela" eginda ere, errazagoa izan daiteke genus desanbiguazioa egitea.

VII.C.4.c) Hiztegietatik erauzitako hierarkien lotzea

Lan honetan, hierarkien eraikuntzan sinonimia erlazioa ez dugu kontuan hartu. Autore gehienek hiztegietatik erauzitako sinonimia erlazioari ez diote jaramonik egin, baina LPPL-ren kasuan sinonimo bidezko definizioak ugariak dira (adiera guztien %20). Artolak (1993) bere HEBan sinonimo ziren adieretan erlazioak sinonimo batetik bestera kopiatzen zituen, eta horren eragina neurtzea interesgarria deritzogu. Bestelako hurbilpenak ere aztertu beharko lirateke: adibidez, WordNet-en sinonimo diren adiera guztiak kontzeptu bakarra osatzen dute.

Nahiz eta hierarkiak lotzeko metodoak etorkizuna duela erakutsi dugun, ez dugu zehatz-mehatz ebaluatu lortzen den hierarkiaren kalitatea. Halakoak ebaluatzeko ez dago gaur egun irizpide finkorik, ez bada hiponimo/hiperonimo lotura bakoitzaren doitasuna, jadanik eman duguna (%82). Neurri hori oso mugatua izanda, aplikazio batetarako –adibidez, informazioaren erauzketa– erabilgarria den edo ez izan daiteke irizpide interesgarria. Bestalde ezin da ahaztu *ANSI ad hoc Ontology Standards Group* delakoa, arestian aipatu duguna, bere zereginen artean ontologiak ebaluatzeko irizpideak lantzen ari dela, oraingoz emaitza gabe.

VII.C.4.d) Sorgin-gurpila

LPPL-WordNet lotura, LPPL-ko genusen desanbiguazioa eta LPPL-ren txapelaren eraikuntzaren artean elkarrekintza konplexuak gerta daitezke. Tesi lan honetan bata bestearen ondoren egin izan dira, baina hiru prozesuen arteko elkarrekintza hobeto aztertu beharko litzateke. Behin LPPL-ko hierarkiak desanbiguatu eta txapelaren bidez lotu ondoren, LPPL-WordNet lotura egiteko informazio gehiago dugu, hierarkiak lotzen ari baikara, eta suposatu daiteke emaitza hobeagoak lortu ditzakegula. Bestalde jadanik aipatu dugu, behin txapela eginda, errazagoa izan daitekeela genus desanbiguazioa egitea. Lotura elebidun hobeekin, bai txapela eta bai genus desanbiguazioa ere hobetu daitezke, eta abar. Prozesu iteratibo bat plantea daiteke.

Bestelako hurbilpen interesgarri bat sare neuronalen eskutik etorri daiteke. Kapitulu honetan deskribatutako emaitza guztiak –LPPL-WordNet lotura, LPPL-ko hiponimo/ hiperonimo erlazioak, WordNet beraren hierarkia– sare neuronal bateko arku bezala errepresenta daitezke. Sare neuronalari energia funtzio egoki bat esleituz gero, ezagunak diren teknikak aplikatu daitezke arkuen konbinazio ezin hobea bilatu dezan. Horrela aldi berean erabakiko luke zein den adiera bakoitzerako WordNet lotura hoberena eta hiperonimo hoberena.

VII.C.4.e) Bestelakoak

EBLen sorkuntza eta aberasketa automatikoa landu dugun arren, ez ditugu horren ikuspuntu guztiak landu. Hutsune nagusietako bat definizioen ***differentia*-tik erauzitako informazioa** (Artola, 1993) landu ez dugula izan da. Differentia-ren erabilera betidanik interesgarritzat jo izan da eta egungo lanek (ikus adibidez, Richardson, 1997) arnas berria eman diote bertatik erauzitako informazioaren erabilgarritasunari. Bestalde, adieren adibideen analisia bultzatu beharko litzatekela uste dugu, adiera azaltzen den testuinguruei buruzko informazio interesgarria ematen dute eta.

Hierarkia eleanitzen eraikuntza automatikoa tesi-lan honetatik gertu dagoen alorra da. Hizkuntza ezberdinetako baliabideak lotzen goazen heinean, hierarkia eleanitzak osatzen ari gara. Inplizituki, ontologia ezberdinetako informazio (erdi-) automatikoki hizkuntza batetik bestera xurgatzea posiblea den edo ez ikertzen ari gara, eta aldi berean hierarkia unibertsalak eraiki daitezkeen edo ez aztertzen. Aldi berean, hierarkia ezberdinetako informazioa bateragarria den edo ez, goi mailak automatiko lotzea komeni ote den, eta antzeko galdera ugari sortzen zaizkigu. Galdera hauek baliabide lexikal egituratuen eraikuntzatik munduaren eta hizkuntzen ereduen azterketara garamatzate.

Euskarari dagokionean, ezin dugu aipatu gabe utzi **Euskal Hiztegiaren** gainean gure taldean egiten ari den lana. Lan horren helburua euskararako Ezagutza-Base zabala sortzea, informazio semantikoan aberatsa. Horretarako hiztegiaren egituraren azterketa egin da eta TEI gidalerroak jarraitzen dituen kodeketara itzuli dugu (Arriola et al. 1995; 1996a; 1996b). Jadanik bukatu dugu izenen definizioetako erlatore berezi eta genusen bilaketa (Agirre et al. 1998a), eta gaur egun aditz eta adjektiboen analisia, adieren adibideen analisia, eta WordNet-en lotura lantzen ari gara. Hurrengo pausoan, VI. kapituluan azaldutako metodoen bidez, izen, aditz eta adjektiboen hierarkien eraikuntzari ekingo diogu, taldeko kide baten tesiaren barruan, atal honetan planteatu ditugun hobekuntzak aplikatzen saiatuz. Bestalde, Euskal Hiztegiko definizioetan erabiltzen den hizkuntzaren azterketa ere martxan dago, oraingo genus eta erlatore bidezko bilaketa bezala. Etorkizun laburrean taldean garatzen ari diren gramatiken bidez, *differentia*-ren azterketari ekingo diogu, taldeko kide baten tesia izango den lanean.

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